Modeling Water Optimization in Jordanian Agricultural Economy

by

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Abstract

The Middle East and North Africa (MENA) is a region that faces many fresh water challenges. The region is endowed with 1% of the world's water resources while hosting 5% of the world's population. A variety of water scarcity indicators consistently rank MENA states as some of the worst in the world. MENA also faces a variety of sociopolitical and geopolitical conflicts that both directly and indirectly stress existing water resources. Therefore, it is especially important to optimize water usage for countries in this region. In this thesis, we focus on the country of Jordan, investigating quantities of agricultural production and trade that would optimize its water usage. To do so, we first use the Water Footprint theory and the idea of virtual water to quantify the water usage based on the domestic production and trade for a particular set of commodities. We then run a multiobjective optimization to determine the optimal quantities of production, import, and export for each commodity that would produce less water usage and more revenue, relative to a baseline year, and account for meeting domestic demand and food security needs. The results show that Jordan, in 2019, could have saved more water and generated more revenue if they reduced the import of apricots, tomatoes, and peaches while also reducing the exports of maize and wheat.

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Chapter 1

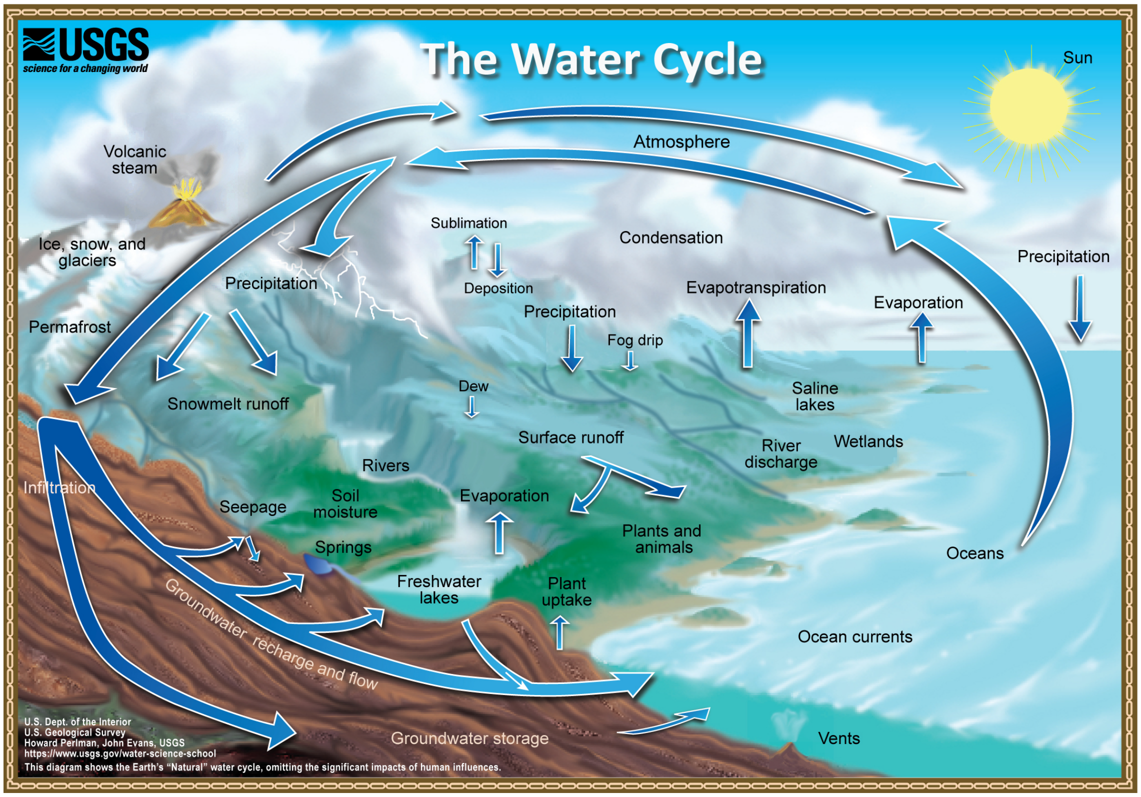
Introduction

1.1 Water

Water is one of the most abundant physical resources on the planet. More than 70% of the surface area of Earth is made up of oceans (Davie 2008, p. 2). At the polar ends of the planet are huge glaciers holding massive volumes of frozen water. Not only is water essential to life for humans, but for countless other animals and vegetation. Even in the atmosphere there are countless particles of water vapor. Water can be used to store and generate power using technology like dams and generators. Because of its low density and viscosity, water enables seamless navigation across the seas and rivers. In turn, and as we will see later, water has significant economic utility for society. Beyond the technological, economical, and other societal benefits, water has paramount significance on culture, religion, and ecosystems across the planet.

Because water is constantly changing forms between solid, liquid, and gas, understanding how water flows on Earth will provide more insight on how to quantify water. The global hydrological cycle, or water cycle, is a conceptual model that helps illustrate how water moves and changes across space and time on the global level and is depicted in Figure 1.1 (Perlman, Evans, and USGS 2019). A standard description of the cycle can be found in Chapter 1 of *Fundamentals of Hydrology* by Tim Davie (Davie 2008, pp. 5-7). We can break down the cycle into two sections: ocean and land. On the ocean, where most of the water is, sunlight heats water causing it to evaporate and condense into clouds. Most of the precipitation from the clouds falls back into the ocean. However, some of it travels to land. On land, the same process happens where water from lakes and rivers evaporate and fall back to land. Trees and plants also have some of their water evaporated in a process called transpiration. Precipitation that falls back into lakes and rivers recharges these water resources and is often called runoff, or discharge. Water that is absorbed by the land percolates through the ground and recharges underground aquifers. Underground water and river water flow back into the ocean and recharge ocean water.

Figure 1.1: Global Hydrological Cycle



One final thing we should note is that water is usually either saline or fresh. While nearly all of the water on Earth is saline water, much of life requires fresh water, especially for human life and activity.

1.1.1 Quantifying Water

Quantifying water is an important research field as it can assess the possibility of "running out of [fresh] water" due to growing population and increasing water withdrawals from underground, river, and lake resources in the past century. The formal quantification of water on Earth restricts to water in forms of solid, liquid, and gaseous states in the atmosphere, surface, and in the crust down to 2000 meters. Estimates reveal that on average across a "long period" of time, 97.5% of all water is saline water and the remaining 2.5% is fresh water. A breakdown of the proportions and quantities of fresh water by source is provided in Table 1.1 (Shiklomanov 1993, p. 13).

Table 1.1: Fresh Water Breakdown

Source	**Volume** (10^3 km^3)	**Fresh Water** (%)
Glaciers and Permanent Snow Cover	24,064	68.7
Groundwater	10,530	30.1
Ground Ice / Permafrost	300	0.86
Lakes	91	0.26
Atmospheric	12.9	0.04
Swamps	11.47	0.03
Rivers	2.12	0.006
Biological	1.12	0.003

For humanity, figures regarding groundwater, lakes, and rivers are the most relevant. On average, it takes about 1500 years for groundwater resources to be completely replenished, or refilled, by the global hydrological cycle compared to 17 years for lakes and 16 days for rivers. (Shiklomanov 2000, pgs. 11-12). Due to the shorter replenishing time for lakes and rivers, these sources are often considered renewable fresh water resources. Additionally, they are more easily accessible to humanity, with a particular emphasis on rivers as they cover more surface area and will have a higher discharge.

There is great temporal and spatial variability of renewable fresh water resources. As can be seen in Table 1.2, more than half of the world's renewable fresh water resources are located in Asia and South America (Shiklomanov 2000, p. 18). This is the case because most of the world's largest rivers are located in these continents. In comparison, most of the world's largest lakes are located in North America. Additionally, about 31% of all river discharge occurs in Asia, 25% in South America, and another 17% in North America (Shiklomanov 1993, pp. 15-16). Temporally, there is inter- and intra-year variation of river discharge: a majority of the discharge might happen during certain months, and some years might produce more volume than others (Shiklomanov 2000, pp. 18-20).

Table 1.2: Average Renewable Fresh Water Resources and Availability Per Capita in 1994

Continent	**Water Resources** ($\frac{km^3}{year}$)	**Availability Per Capita** ($\frac{km^3}{year}$)
Asia	13,510	3.92
South America	12,030	38.2
North America	7,890	17.4
Africa	4,050	5.72
Europe	2,900	4.23
Australia and Oceania	2,400	83.7
The World (Rounded)	42,780	7.60

Water withdrawal and water consumption are two important but different concepts. Withdrawal refers to the water extracted from a source while consumption refers to the portion of withdrawal that has to undergo the global hydrological cycle to be withdrawn again (Reig 2013). Consumption is a subset of withdrawal because consumption *requires* withdrawing. An example of water withdrawal is when a company that operates hot machinery uses water for cooling. While water has to be withdrawn first for the company to use it, most of the water is not consumed and could be returned to the source or further used for consumption. On the other hand, an example of water consumption is when a farmer extracts their water from an underground source. Nearly all of the water they withdraw ends up being consumed by their crops, which will later end up in the global hydrological cycle.

Withdrawal and consumption of water occur in agricultural, municipal, and industrial sectors of the society. In 2000, it was estimated that agriculture receives

66% of global water withdrawals and 85% of global water consumption (Shiklomanov 2000, pgs. 23-24). Most of the water consumption happens in Asia as that is where most of the arable land is. The figures, of course, have great spatial disparity as certain nations have higher populations or have access to more water sources. Withdrawals are also linked to economic status because more advanced equipment leads to higher withdrawal values. With the exception of South America, there are simultaneously high and low water withdrawals in the regions of every continent.

1.1.2 Virtual Water and Water Footprint

"Virtual water" is defined as "water needed to produce agricultural commodities" (Allan 2003, p. 5). The concept was first proposed by Allan 1997, motivated by research of the politics and economics of the Middle East and North Africa (MENA, more details in Section 1.2) region. It is concluded that trading food was equivalent to trading (virtual) water, which is a very limited but essential resource in the region. For water-scarce nations, viewing food trade as *virtual water trade* provides an economical insight to a physical resource problem. Virtual water can be measured as a rate of volume per unit, like virtual water content, or rate of volume per time period, like virtual water trade. These concepts became adapted and formalized for broader usages in Hoekstra et al. 2011.

Suppose a specific nation has limited access to fresh water resources. A Commodity C can be water-intensive, meaning C requires more water to produce in this nation when compared to producing in other nations. Another interpretation is the *virtual water content* of C in the specific nation is high while in other nations it is low. The utility of virtual water comes in when we consider if the specific nation can substitute the need for producing C domestically by importing it instead. Instead of spending water, the nation could spend its capital to obtain C, potentially resulting in massive water savings. In this context, the said nation is utilizing *virtual water imports* of C. Conversely, the foreign nations trading with the specific nation is utilizing *virtual water exports* of C. For nations that have limited fresh water resources, having high virtual water imports might also be essential for survival. For example, Allan and Olmsted 2003, p. 59 predicted that by the year 2050, half of all water consumed in the MENA region will be from virtual water trade of cereal.

The idea of minimizing water consumption by maximizing the utility of virtual water imports is enticing. It might be entirely plausible that importing a commodity C is cheaper and more efficient for a country than it is to self-produce, sell, and export the commodity. However, maximizing virtual water imports is not always ideal. For example, in terms of food security, it is not a good idea for MENA to be entirely dependent on trade to meet its needs for essential commodities like cereal crops. While it may be strategic to save water, it can result in detrimental consequences as finding the desired trading partner is not always guaranteed but feeding your population is.

To quantify the consumption of water in society, we utilize the Water Footprint theory, which is considered the global standard (much like the concept of the Carbon Footprint). Not only does the Water Footprint theory allow quantification of water consumption for agricultural commodities, but industrial, processed, and livestock as well. Additionally, the theory details how to determine the water footprint of any general process and general entity, including within a geographically delineated area like a river basin, province, or nation. The water footprint of a commodity, like crops and industrial products, is the volume of water consumption needed to produce a unit of that commodity. The water footprint is (largely) composed as the sum of the blue and green water footprints, or blue and green water consumption. Blue water consumption refers to direct water consumption, usually in the form of surface or groundwater withdrawal. Green water consumption refers to indirect water consumption, usually in the form of precipitation. Since precipitation can vary by time and location, the water footprint of a commodity varies temporally and geographically. The total water consumption associated with the production of a commodity during a given year can be calculated by multiplying the water footprint of the commodity by the units of the commodity produced in that year.

We note that *water consumption* is not entirely the same thing as *water usage*. Consider Commodity C being produced in a nation. Water had to be consumed to produce C, and because the nation produced the commodity domestically, it has the burden of the associated water usage. In this context, when a commodity is produced within the target nation, water consumption and water usage are the same thing and both would be positive values. However, the distinction comes in when we incorporate trade. Suppose C was imported from some foreign nation. If we assume C was produced in the foreign nation, then the target nation would have a negative water usage value, as it did not use any water to produce C and saved water, while the foreign nation would have a positive water usage value, as it was spending water to produce C. In our analysis, we are interested in water usage because that is the value that measures the amount of actual water that is being consumed by a nation to produce commodities. Additionally, we refer to water usage of commodities relative to trade as virtual water. We elaborate on these concepts further in the Method section.

In short, the Water Footprint theory allows for quantification of all types of water consumption in society. In terms of domestic production of commodities, water consumption and water usage are the same thing. However, they are slightly different concepts when trade is taken into consideration. Consistent with the concept that traded commodities have water consumption associated with them called virtual water content, we refer to the water usage of commodities in trade as virtual water.

1.1.3 Water Conflict

There are three main reasons why water leads to conflict (see Libiszewski 1995). Firstly, water is a limited natural resource. Resources found in nature may be abundant due to the sheer size of the planet, but their availability varies. As stated earlier, humans get a majority of their water from rivers, but not every nation or region has equal access to rivers relative to a cluster of factors like population, river discharge contribution, and percentage of river in territory. The nations that do not have abundant access to rivers will have to rely on aquifers and desalination technology, if they can afford it.

Secondly, water is a transboundary resource. When a resource falls within a nation state boundary, there is little to no debate of who owns the resource: it is the nation encompassing the resource. The issue becomes complicated when a resource crosses one or several other nations. Lakes and rivers often cross several boundaries and even serve as boundaries between nations. We should not forget that aquifers, despite not on the surface, can span across several nations as well. Also, there is a fundamental geographical problem with water: it flows from high to low elevation and flow contribution is typically the greatest at the origin. This implies that downstream riparians are automatically at a disadvantage when negotiating their transboundary water rights due to their dependence on the river.

Lastly, water is essential for life. While dietary preferences can be accommodated for, there is no substitute for water. Due to population growth, the demand for water will generally increase and the natural supply is limited. Water is an extremely inelastic good because there are no easily available substitutes; it is something society needs regardless of its price or availability (Metaxas and Charalambous 2005).

Controlling the supply of water is not just a control over the livelihood of society, but also the economy.

Overall, conflict regarding water arises due to how unevenly fresh water sources are spatially distributed across the planet. These sources often border several other nations and give a geographically unfair advantage to the upstream riparians. Water is a fundamental and precious natural resource, securing access to it is essential to the survival of a nation. Therefore, it is no surprise that nations are willing to engage in military combat over water.

1.2 Middle East and North Africa

The Middle East and North Africa (MENA) is a set of nations in Northern Africa and Western Asia. Besides similarities in language, culture, and colonial history, MENA states also share problems with water scarcity.

MENA states are some of the hottest places on Earth (Saunders 2023). This comes at no surprise as geographically, MENA is situated just north of the Equator in a region known as the Tropic of Cancer. The Tropic of Cancer–due to Earth's tilted axis and irregular shape–receive more radiation from the sun than any other part of the planet, on average (Sobel 2012). Some of the largest hot deserts in the world reside in MENA. Because of how arid the climate is and the lack of moisture and precipitation, droughts are common. Climate change will also continue to have devastating consequences for the region; rising temperatures and sea levels will put further strain on MENA in aspects like housing, agriculture, and fresh water availability (Wehrey and Fawal 2022). In addition, the population of MENA is increasing and currently represents 5% of all mankind on 10% of all land in the world with 1% of the world's water resources (Badran, Baydoun, and Murad 2017,

p. 58; Roudi-Fahimi 2001; Waterbury 2017, p. 58). More people being born means more water consumption. All these factors collectively contribute to the growing concern of water scarcity in the region.

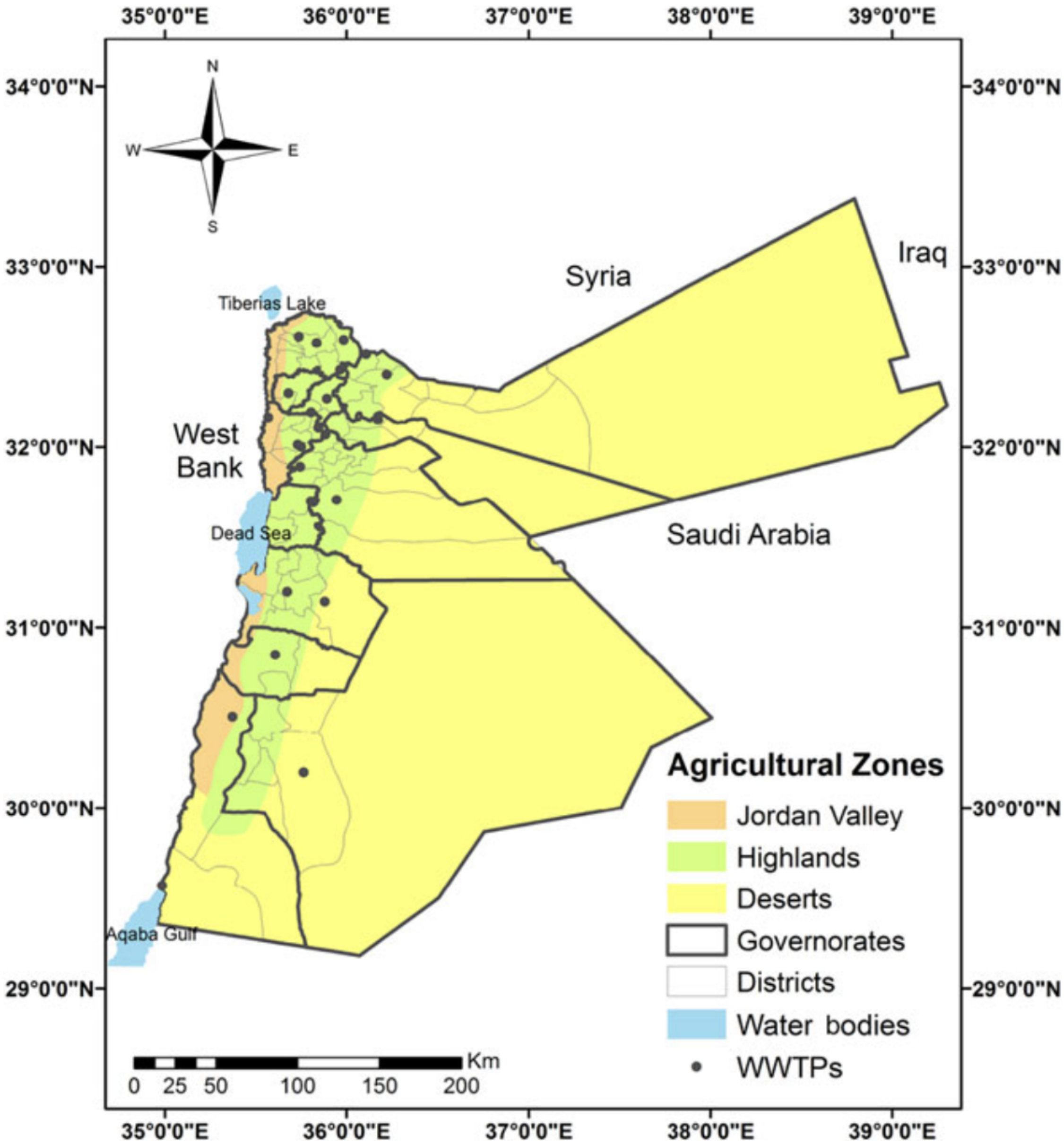
As mentioned earlier, existing fresh water resources have incredible variability because of seasonal fluctuations that contribute to droughts and floods. Many scholars have attempted to quantify water scarcity among more than 150 different indicators (Hussain et al. 2022, p. 932). Several existing analyses conducted have determined MENA is water scarce. According to the Water Crowding Index (WCI), most MENA states are between stress and absolute scarcity (Jemmali and Sullivan 2014, fig. 3). Under the Water Stress Index (WSI), MENA is considered overexploited (Smakhtin, Revenga, and Döll 2004, fig. 6). More holistic indicators like the Social Water Stress/Scarcity Index (SWSI) rank Northern Africa, Iran, Iraq, Syria, and Lebanon to be among the worst in terms of water scarcity while the majority of the Gulf region being some of the best (Jemmali and Sullivan 2014, fig. 5). All indicators of water scarcity factor in extraction of physical water resources, especially rivers. In summary, the literature indicates that MENA is on the extreme end of water scarcity. The exceptions are the Gulf States and Israel who use advanced desalination technology to meet a majority of their water needs even though they face physical water scarcity that is comparable to the rest of the region (Badran, Baydoun, and Murad 2017; Waterbury 2017, p. 79). Interestingly, Allan 1997, p. 3 argues MENA "ran out of water" in the 1970s and since then has been meeting agricultural needs through imports.

The three main river basins in MENA are the Nile, the Jordan, and the Euphrates-Tigris River. While there exist tributaries of these rivers as well as other smaller rivers, these three are the most reliable and natural sources of fresh water in the region. However, some MENA states are not riparians to any of the major river basins and so obtain their fresh water through the next two most popular means: aquifers and desalination plants. All MENA states use aquifers and some of the largest span across Libya and Algeria, Israel and the Palestinian Territories, and Saudi Arabia (Fanack Water 2022). Aquifers are under stress and it is feared that MENA states are extracting more groundwater at rate faster than it is being replenished (Tropp 2007). Wealthier states tend to rely more on desalination plants. For example, Saudi Arabia satisfies as much as 60% of their fresh water needs through their desalination operations (Fleck 2023). Although lakes and aquifers are frequently transboundary sources of fresh water that are also contested, this analysis focuses only on the Jordan River basin as Jordan is the nation of interest.

1.2.1 Jordan

We choose to perform our analysis on the Hashemite Kingdom of Jordan, or Jordan. Jordan borders Israel, the West Bank, Syria, Iraq, and Saudi Arabia. Like many other MENA nations, the climate is arid with little precipitation. Geographically, Jordan can be divided into the Jordan Valley (JV), Highlands, and Deserts, as seen in Figure 1.2 (Talozi, Al Sakaji, and Altz-Stamm 2015, fig. 1). Deserts cover 75% of the nation (UNFPA 2016).

Figure 1.2: Map of Jordan and Regions



In 2020, the Ministry of Water and Irrigation published a report titled "Jordan Water Sector: Facts and Figures" elaborating on a variety of statistics from the past decade (Ministry of Water and Irrigation 2020). Jordan can be classified into 15 surface water basins and 12 groundwater basins (or aquifers). Of the 15 basins, 12 are being depleted at a rate faster than what they can be recharged at. In 2020, 53% of all water came from groundwater sources while 32% came from surface water sources. Since 2010, groundwater consumption in units of million cubic meters (MCM) has been 1.5x greater than surface water consumption. In 2020, 51% of all water consumption was for agricultural needs while 46% was for domestic needs. Of the 51% of agricultural water consumption, 35% came from groundwater sources.

Agriculture is of particular importance to Jordan. Agriculture accounts for as much as 30% of the nation's GDP "when considering activities related to agricultural production upstream and downstream of the value chain" (Perosino 2023, pp. 5-6). Most agricultural activity happens in the JV—due to close proximity of the Jordan River—and regulations on water consumption from the river are often controlled by the Jordan Valley Authority (JVA), a "state within a state" (Perosino 2023, p. 10). The Northern JV is largely fruits trees and the Central JV is primarily made up of vegetable farms. Precipitation and temperatures inversely change as we reach the Lower JV, causing crops like Medjhoul dates (dried dates) to be popular. Interestingly, bananas are very popular in the Lower JV despite how water-intensive they are. In the 80s, the JVA stopped distributing licenses to plant bananas, but attempts were generally unsuccessful due to banana producers being a powerful lobby (Perosino 2023, p. 11).

However, Jordan, like many other Arab nations, is extremely dependent on food imports, especially of goods needing processing like sugar, corn, rice, barley, and wheat. Cereal crops like corn, rice, barley, and wheat are generally considered staple crops and hence essential for any nation.

1.2.2 The Jordan River

The Jordan River can be thought of as two parts: the Upper Jordan River, or Hula Valley, and the Lower Jordan River. A detailed map of the basin is shown in Figure 1.3 (FAO and IHE-Delft 2020, fig. 1). The main flow of the Jordan comes from the Hula Valley, which resembles the convergence of three three rivers: the Hasbani River in Lebanon, the Banias River in the occupied Syrian Golan Heights (northeast of Lake Tiberias), and the Dan River in Israel (UN-ESCWA and BGR 2013, p. 177). These rivers emerge from the Anti Lebanon Mountains, specifically Mount Hermon, and the largest contributing tributary is the Dan River. The Hula Valley flows down into Lake Tiberias, or the Sea of Galilee. From the Sea of Galilee to the Dead Sea forms the Lower Jordan River. One major tributary that contributes to the Jordan is the Yarmouk River, which originates in Syria (UN-ESCWA and BGR 2013, p. 178). The entire Jordan River system forms a natural border between Israel and Syria, Israel and Jordan, and Jordan and the West Bank. Statistically, in term of the river and all of its tributaries, 40% of the Jordan River resides in Jordan, 37% in Syria, 10% in Israel, 9% in the West Bank, and the remaining 4% in Lebanon (UN-ESCWA and BGR 2013, p. 177).

Figure 1.3: Jordan River Basin Map

Origins of the Jordan River basin conflict can be traced back to the establishment of Israel in 1948. From 1949-53, Israel attempted the construction of several hydrological projects like the National Water Carrier in demilitarized zones in Syria but faced pushback by Syria, leading to the initial series of military conflicts between the nations. These projects interrupted Jordanian, Lebanese, Syrian hydrological plans for the river basin as well (Haddadin 2014, p. 246; UN-ESCWA and BGR 2013, p. 194). Due to this and the growing Arab-Israeli tensions, the U.S. attempted to mediate and proposed the Johnston Plan to partition water consumption of the basin among the riparians, though this plan was never ratified. Instead, the U.S. financially supported both Israeli National Water Carrier and King Abdullah Canal (previously known as the East Ghor Main Canal) hydrological projects along the basin in hopes of easing tensions between Israel and Jordan. However, parts of the Jordanian project were seen as unfavorable to Israel. As the former Jordan Minister of Water and Irrigation Munther J. Haddain said, "the less efficient the water diversion to Jordan, the greater the flow to Israel" (Haddadin 2014, pp. 250-251). This conflict, along with the Syrian plan to divert water from the Hasbani and Banias Rivers to the Yarmouk, were precursors to the 1967 war (Seliktar 2005, p. 61; UN-ESCWA and BGR 2013, p. 194).

After the Six Days War, Israel controlled all of the Upper Jordan and parts of the Yarmouk. As a result, Jordan became even more dependent on the Jordan River as Israel solidified its influence on the Lower Jordan (Zawahri 2010, pp. 131-132). In 1994, Israel and Jordan signed a peace treaty that benefited them but excluded their neighbors (Haddadin 2014, pp. 256-259; Susskind and Islam 2022). Because the nature of the Israeli-Jordanian conflict was around allocation quotas, building of storage, and diversion facilities on a shared river basin, Libiszewski argues the water dispute, at least since 1988, is a "genuine water conflict" rather than one around politics or border rights (Libiszewski 1995, p. 46). Libiszewski believes this conflict to be genuine because the resources in question are of the same national importance economically for all parties involved (Libiszewski 1995, p. 50).

Jordan and Syria also have conflict due to their shared use of the Yarmouk River. In 1953, the two nations agreed to the construction of several dams along the river in hopes of generating electricity and storing water. Due to the Israeli occupation of the Golan Heights in 1967, new agreements were signed in 1987 and 2000. All three were regarding the construction of dams and did not allocate flow quantities, placed nearly all the financial burden on Jordan, and assured Syria's access to the springs feeding the Yarmouk (Zawahri 2010, pp. 136-138). These projects led to controversy as the Yarmouk River flow declined over time. Jordan blames Syria as they built more dams than agreed on in 1987 and Syria passes the blame to climate change. One independent study found that the main cause was groundwater extraction by Syrian highland farmers (Avisse et al. 2020). Such unregulated extractions have been rampant across MENA due to the high dependency of aquifers (Sowers, Vengosh, and Weinthal 2011, p. 609; Tropp 2007). Even without the Yarmouk, Syria has the Euphrates to rely on. Jordan, on the other hand, does not have many other options as the Jordan River is partially fed by the Yarmouk River. It does not help when the overall Jordan River basin flow is decreasing even though Jordan's shared allocation of the Yarmouk with Israel from their 1994 agreement remains the same (Avisse et al. 2020; UN-ESCWA and BGR 2013).

The conflict surrounding the Jordan River basin is the most complex in all of MENA. In a small and confined area of cultural and religious significance, the water resources are arguably the most depleted. If Syria eased their control of the Yarmouk, then they could still rely on the Euphrates. Even then, Jordan has successfully negotiated with Israel in the past and have been on relatively good terms since and so make collaboration along the Jordan River more feasible. While Israel already meets 50% of its fresh water needs from its desalination plants, Jordan is hoping to get a large plant operational by 2028 that will have a "continuous water supply, 24/7, so people will no longer have to ration water" (Kramer et al. 2022, p. 1; Vidon 2023).

1.3 Existing Literature and Our Contribution

Several assessments on water footprints and virtual water trade have been done at the global scale that not only look at crops, livestock, crop and livestock derivatives, and industrial products as well (Chapagain and Hoekstra 2008; Hoekstra 2003; M. M. Mekonnen and Hoekstra 2011; Mesfin M. Mekonnen and Hoekstra 2012). Studies have been specifically done on MENA to quantify and optimize water consumption, usage and trade. Ewaid, Abed, and Al-Ansari 2020 quantified the water footprints and water consumption of cereal crops like barley, maize, rice, and wheat of Iraq by province. Their research also incorporated virtual water imports and the amount of land and water the nation saves by importing these commodities. Similarly, Muratoglu 2020 quantified the water consumption of wheat in Turkey by province while also incorporating net virtual water savings from trade. Ababaei and Ramezani Etedali 2017 performed an assessment to quantify water consumption of Iran by province for production of barley, rice, and wheat.

Regarding optimization, Wahba, Scott, and Steinberger 2018 quantified the virtual water trade and water footprint of Egypt through a bottom-up approach using an inter-regional input-output (IRIO) model between Egypt and the world. Maroufpoor et al. 2021 performed a multiobjective optimization for Iran determine cropping patterns that would consume less water and address food security concerns in an inter-trade network of Iranian provinces. Similarly, Huang et al. 2023, Sedghamiz et al. 2018, and Delpasand et al. 2023 conducted multiobjective optimizations with the latter two using game theory approaches to select the best solutions from a solution set. On a global scale, Chouchane, Krol, and Hoekstra 2020 performed a linear optimization to reduce blue water consumption of the world's most severely water-scarce regions while keeping global crop productions unchanged and agricultural land used per nation from increasing.

Regarding analyses of Jordan, Al-Weshah 2000 aimed at optimizing irrigation water usage in the Jordan Valley by conducting a single objective optimization analysis to maximize revenue of agricultural production while constraining for land, water usage, and food security. Other analyses by Abu-Sharar, Al-Karablieh, and Haddadin 2012 and Mourad, Gaese, and Jabarin 2010 looked at quantifying profitability of various crops in Jordan while also including virtual water imports and exports into their analysis. A more interdisciplinary analysis was done by Talozi, Al Sakaji, and Altz-Stamm 2015 which looked at how Jordan can utilize virtual water at the intersection of water, energy, and food to make more efficient and knowledgeable policy decisions.

In our analysis, we apply a similar multiobjective optimization model that Delpasand et al. 2023 used, but to Jordan. Unlike other models, they consider optimizing two objectives simultaneously by modifying both production and trade quantity values. Our model optimizes trade quantity values at the nation level. Additionally, we do not employ any game theory approaches like Delpasand et al. 2023 to select the best optimal solutions from the solution set.

Chapter 2

Method

We utilize economic and trade information related to Jordan for a set of agricultural commodities in 2019. First, we determine the baseline revenue contribution and water usage relative to these commodities. We use the revenue rates—or USD per unit—for domestic sales, international imports, and international exports to calculate the baseline revenue contribution. We use the water footprint rates—or volume of water usage per unit for each commodity—to calculate water usage. The optimization model is designed to answer the following question: if we fixed the revenue and water footprint rates, what are other quantity values of domestic production, import, and export for each commodity that overall generate more revenue and use less water relative to the baseline year? Additionally, each potential solution is vetted to assure the aggregate domestic demand from the baseline year is met along with our food security constraint, which requires that at least a quarter of aggregate domestic demand is met through domestic production. To perform this analysis, we rely on the Water Footprint theory to quantify water usage of commodities in production and trade. Additionally, we rely on optimization theory and the NGSA-II algorithm to solve the multiobjective optimization problem.

2.1 Water Footprint Theory

The Water Footprint theory details how to measure the water footprint of agricultural commodities. In agriculture, blue water is irrigation and green water is precipitation. We utilize the CROPWAT model, which was developed by the Food and Agricultural Organization (FAO), to calculate blue and green water usage of crops (M. Smith 1992). The CROPWAT model incorporates the concept of crop evapotranspiration, which is the the amount of water a crop utilizes to grow. The FAO has established the standard for calculating crop evapotranspiraton in their book *Crop Evapotranspiration: Guidelines For Computing Crop Water Requirements* (Allen et al. 1998). One option of using the CROPWAT model is through the Crop Water Requirements (CWR), which assumes the amount of water a crop *needs* is equal to the amount of water it *uses*. In other words, we assume there is no water limitation to crop growth, among other factors. While such an assumption might be unreasonable for analysis in MENA due to the arid climate, we utilize this option in our analysis as it greatly simplifies calculations. It should be noted the CROPWAT model comes with accompanying software to assist with calculations, but we chose not to use the software. Instead, we implemented a modified version of the model in R.

2.1.1 Water Footprint of Crops

The water footprint of crop c, denoted WF_c, is the virtual water content or the amount of water needed to produce a unit of a crop c. For the sake of simplicity, the subscript c is implicit throughout the manuscript. WF is measured in the unit of $\frac{\mathrm{m}^3}{\mathrm{tonne}}$ and can be calculated as the sum of the blue and green water footprint.

Specifically,

$$
\begin{aligned}
WF &= WF_{blue} + WF_{green} \\
&= \frac{CWU_{blue}}{Y} + \frac{CWU_{green}}{Y} \\
&= \frac{10 \cdot ET_{blue}}{Y} + \frac{10 \cdot ET_{green}}{Y},
\end{aligned}
\tag{2.1}
$$

where CWU is the crop water usage (m^3 per unit area), Y is the yield of crop (tonne per unit area), and ET is the evapotranspiration rate of crop c, which represents the amount of water a crop needs during its growth cycle. Note that the standard unit for ET is millimeters (mm) and the conversion factor 10 is given in the FAO handbook to convert ET to CWU (Allen et al. 1998).

For blue (i.e., direct, irrigation) water, ET is equivalent to the irrigation requirement (IR) and can be calculated as

$$ET_{blue} = \max(0, CWR - P_{eff}),$$

where CWR is the crop water requirement (in the units of mm, which is an aggregation of ET over time; for our model, monthly data is used), P_{eff} is the effective rainfall during the period of crop growth (in the units of mm), calculated as

$$P_{eff} = \begin{cases} 125 + 0.1 \cdot P_{month} & P_{month} > 250 \\ \frac{P_{month} \cdot (125 - 0.2 \cdot P_{month})}{125} & P_{month} \leq 250 \end{cases},$$

and P_{month} is the aggregate precipitation for the month. If P_{eff} is greater than CWR, then no irrigated (blue) water is needed for crop c. For green (i.e., indirect, precipitation) water, ET is calculated as

$$ET_{green} = \min(CWR, P_{eff}).$$

An important quantity in the above calculation is a crop-specific evapotranspiration rate ET_c. The FAO has proposed several methodologies to calculate this value. As discussed earlier, we utilize the CROPWAT model. The model assumes that the crop c is "a disease-free crop, growing in a large field (one or more hectares) under optimal soil conditions including sufficient water and fertility and achieving full production potential of that crop under the given growing environment" (Allen et al. 1998, p. 87). Specifically, we express ET_c as

$$ET_c = ET_o \cdot K_c, \tag{2.2}$$

where ET_o is the evapotranspiration of a *reference* crop on a reference surface in the units of $\frac{\text{mm}}{\text{day}}$ and K_c is the dimensionless *crop coefficient*. In the following sections, we discuss these two values in detail.

The ET_o Value

ET_o, as stated earlier, is the evapotranspiration of a reference crop on a reference surface. The FAO defines the reference crop and surface as the following: "The reference surface is a hypothetical grass reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 s m-1 and an albedo of 0.23. The reference surface closely resembles an extensive surface of green, well-watered grass of uniform height, actively growing and completely shading the ground. The fixed surface resistance of 70 s m-1 implies a moderately dry soil surface resulting from about a weekly irrigation frequency" (Allen et al. 1998, p. 15).

There are several methods for calculating ET_o, but the standard is the FAO Penman-Monteith (P-M) equation which requires radiation, air temperature, air humidity, and wind speed data. According to the P-M equation, the evapotranspiration of a reference crop or ET_o is expressed as the following:

$$ET_o = \frac{0.408 \cdot \Delta \cdot (R_n - G) + \gamma \cdot \frac{900}{T+273} \cdot u_2 \cdot (e_s - e_a)}{\Delta + \gamma \cdot (1 + 0.34 \cdot u_2)}, \tag{2.3}$$

where

- Δ ($\frac{\text{kPa}}{°C}$) is the slope of the saturation vapor pressure-temperature curve at the average air temperature,
- R_n ($\frac{\text{MJ}}{\text{m}^2 \cdot \text{day}}$) is the net radiation at the crop surface,
- G ($\frac{\text{MJ}}{\text{m}^2 \cdot \text{day}}$) is the soil heat flux density,
- γ ($\frac{\text{kPa}}{°C}$) is the psychometric constant,
- T ($°C$) is the average air temperature at 2 meters above the crop surface,
- u_2 ($\frac{\text{m}}{\text{s}}$) is the wind speed at 2 meters above the crop surface,
- e_s (kPa) is the saturation vapor pressure,
- and e_a (kPa) is the actual vapor pressure.

Each parameter has either one or more formulae which may vary depending on the time series. Many parameters have overlapping data requirements while some allow substitution of other variables for less accuracy. We utilize the relevant equations for a monthly time series analysis as that is highest temporal resolution available for our data. In practice, each of the variables are calculated as follows, where a monthly average is used for all the relevant measurements.

- Δ

We calculate Δ with the following equation:

$$\Delta = \frac{4098 \cdot (0.6108 \cdot \exp(\frac{17.27 \cdot T}{T+237.3}))}{(T+237.3)^2},$$

where T ($^\circ C$) is the air temperature at 2 meters above crop surface.

- R_n

  We calculate R_n with the following equation:

  $$R_n = R_{ns} - R_{nl},$$

  where R_{ns} ($\frac{\text{MJ}}{\text{m}^2 \cdot \text{day}}$) is the incoming net shortwave radiation and R_{nl} ($\frac{\text{MJ}}{\text{m}^2 \cdot \text{day}}$) is the outgoing net long-wave radiation.

  The equations for R_{ns} and R_{nl} are extremely tedious but involve the following variables: latitude, elevation above sea level, month of the year, average hours of sunshine, and temperature.

- G

  Assuming a constant soil heat capacity of 2.1 $\frac{MJ}{\text{m}^3 \cdot {}^\circ C}$ and an appropriate soil depth, we calculate G for month i with the following equation:

  $$G_i = \begin{cases} 0.14 \cdot (T_i - T_{i-1}) & \text{if } T_{i+1} \text{ is unknown} \\ 0.07 \cdot (T_{i+1} - T_{i-1}) & \text{else} \end{cases},$$

  where T_i ($^\circ C$) is the air temperature at 2 meters above the crop surface at month i. Calculating G for a monthly time series requires at least 3 consecutive values for air temperature.

- γ

We calculate γ with the following equation:

$$\gamma = 0.000665 \cdot P,$$

where P (kPa) is the atmospheric pressure. We calculate P using the following equation:

$$P = 101.3 \cdot \left(\frac{293 - 0.0065 \cdot z}{293}\right)^{5.26},$$

where z is the elevation above sea level in meters.

- T

  We calculate T with the following equation:

  $$T = \frac{T_{min} + T_{max}}{2},$$

  where T_{min} $(°C)$ and T_{max} $(°C)$ are the minimum and maximum temperatures, respectively.

- e_s

  We calculate e_s with the following equation:

  $$e_s = \frac{e^0(T_{min}) + e^0(T_{max})}{2},$$

  where $e^0(T)$ (kPa) is the saturation vapor pressures at the air temperature at 2 meters above the croup surface. The general formula for $e^0(T)$ is calculated as follows:

  $$e^0(T) = 0.6108 \cdot \exp\left(\frac{17.27 \cdot T}{T + 237.3}\right).$$

- e_a

There are four relevant formulas to calculate e_a. They are listed below in order of preference:

- Formula 1

  Assuming we have values for minimum and maximum relative humidity values as decimal percentages, we calculate e_a as follows:

$$e_a = \frac{RH_{max} \cdot e^0(T_{min}) + RH_{min} \cdot e^0(T_{max})}{2},$$

  where RH_{max} and RH_{min} are maximum and minimum relative humidity values as decimal percentages, respectively.

- Formula 2

  Assuming we only have RH_{max}, we use the following modified equation:

$$e_a = RH_{max} \cdot e^0(T_{min}).$$

- Formula 3

  Assuming we only have the relative humidity value as a decimal percentage, we use the following modified equation:

$$e_a = RH_{mean} \cdot \frac{e^0(T_{min}) + e^0(T_{max})}{2},$$

  where RH_{mean} is the average relative humidity value as a decimal percentage.

- Formula 4

Assuming we only have T_{min}, we use the following modified equation:

$$e_a = e^0(T_{min}).$$

It will be helpful to think of ET_o as a curve when programming and performing the computations.

The K_c Value

If we recall, ET_o is an estimation of the evapotranspiration of a reference crop. To determine the water requirements for other crops, ET_o is multiplied by K_c, or the crop coefficient. The K_c value encapsulates the unique water needs of a crop c, including things such as the crop type, climate, soil evaporation, and crop growth stages.

Because the unique water requirements of a crop vary depending on the growth stage, K_c is a function of time, usually in days. Therefore, it is more appropriate to refer to K_c as the crop coefficient curve. Calculating the curve requires knowing the length of the growing stages of a crop and the corresponding K_c coefficients at each stage. In general, there are four growth stages of any crop: initial (L_{init}), development (L_{dev}), middle (L_{mid}), and late (L_{late}). Each stage is an integer number of days long and the sum of the length of the development stages equals the total number of days required to fully grow a crop. Note that these stages will vary depending on the cropping pattern.

Consistent to the growth stages of any crop, the domain of the K_c curve is divided into four intervals. During L_{init}, the value of K_c is equal to the coefficient $K_{c\ init}$. During L_{dev}, K_c is a linear interpolation between the coefficients $K_{c\ init}$ and $K_{c\ mid}$. During L_{mid}, K_c is equal to $K_{c\ mid}$. During L_{late}, K_c is a linear interpolation between the coefficients $K_{c\ mid}$ and $K_{c\ end}$. Mathematically, the K_c value at day i of the growing season can be expressed as

$$K_{c\ i} = K_{c\ prev} + \frac{i - \sum L_{prev}}{L_{stage}} \cdot (K_{c\ next} - K_{c\ prev})$$

where $K_{c\ prev}$ and $K_{c\ next}$ are the crop coefficient values of the previous and next stages, respectively, $\sum L_{prev}$ is the sum of the lengths of all the previous stages, and L_{stage} is the length of the stage under consideration (Allen et al. 1998, p. 132). Note that the coefficients $K_{c\ init}$, $K_{c\ mid}$, and $K_{c\ end}$ are dimensionless and may vary depending on additional climatic variables.

2.1.2 Trade

According to the Water Footprint theory, the water consumption associated with trade of a nation is called the *virtual water balance*—or virtual water consumption from trade—denoted by V_{net}, which is the difference in virtual water imports and virtual water exports, typically defined as $V_{net} = V_i - V_e$. The total water consumption of a target nation is calculated as $WF = P + V_{net}$, where P is the water consumption associated with domestic production (in the same time period used to determined V_{net}). For our analysis, however, this calculation is not intuitive. Consider the scenario where a target nation does not domestically produce anything and exclusively imports everything. According to the equations above, the target nation would have a positive V_{net} value. However, the nation doesn't actually consume any water, and it in fact has saved water because the water used to produced the imported commodities is not from the the target nation. To that end, as we want to model water usage and not water consumption, we reverse the calculation of V_{net}

as

$$V_{net} = V_e - V_i. \tag{2.4}$$

Doing so implies that V_{net} measures virtual water usage from trade and WF measures total water usage. As a result, for the hypothetical scenario above, a negative value for WF would be produced, which represents the amount of water the nation did not use, or the amount of water usage saved. We should note that the modified definition of V_{net} is similar to the calculation of net revenue in economics, typically calculated as exports − imports.

To calculate V_i and V_e, we assume the amount of water necessary to produce an imported or exported commodity is equal to the amount necessary to produce that commodity domestically. Additionally, we make the assumption that imported commodities are not exported later (no re-exports). These assumptions ensure that we can calculate the water footprint of a commodity without location-specific data. In addition, V_{net} is a function over time, but we use the term to refer to the aggregated consumption (over a year period, measured in m^3) in this analysis.

2.2 Optimization Theory

Optimization is an incredibly useful concept. We want to optimize because we want the "best" solution according to some specific metric. In this section, we first introduce the mathematical formation of an optimization problem in general, and then elaborate on the multiobjective optimization models. We also discuss how multiobjective optimization problems are solved using genetic algorithms and describe the algorithm of our choice: NSGA-II. The notation and theory regarding mathematically expressing optimization problems have been mainly adapted from Kochenderfer and Wheeler 2019 and Jaimes, Zapotecas-Martínez, and Coello 2011.

2.2.1 General Optimization Problem

An optimization problem requires a function to optimize, which we call the *objective function*. We express an objective function f as the following:

$$f : \mathcal{X} \to \mathbb{R},$$

where $\mathcal{X} \subseteq \mathbb{R}^n$ is called the *feasible domain* or *feasible set*. An element of the feasible set is called the *design point* and is denoted by $\mathbf{x}$. In many real-world problems, the entire feasible set is not considered. Instead, the domain of f is *constrained* using inequalities. Though equality constraints could be used, they can be re-written as inequalities. Consider the following constraint function h and a scalar $a \in \mathbb{R}$:

$$\begin{cases} h(\mathbf{x}) - a \leq 0 \\ h(\mathbf{x}) - a \geq 0 \end{cases} \iff |h(\mathbf{x}) - a| = 0.$$

While set membership could be utilized to constrain the feasible set or domain, inequality constraints are more efficient and common.

Under the objective function f, we wish to find the *optimal solution* or design point $\mathbf{x}^* \in \mathcal{X}$ that would achieve the desired optimization, i.e.,

$$\underset{\mathbf{x} \in \mathcal{X}}{\text{minimize}} \quad f(\mathbf{x}).$$

While objectives functions are typically written to be minimized, we can simply negate the output of the objective function for maximization. In general, the design point $\mathbf{x}$ can be of dimension n. We can fully express the design point as the following:

$$\mathbf{x} = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix}^T,$$

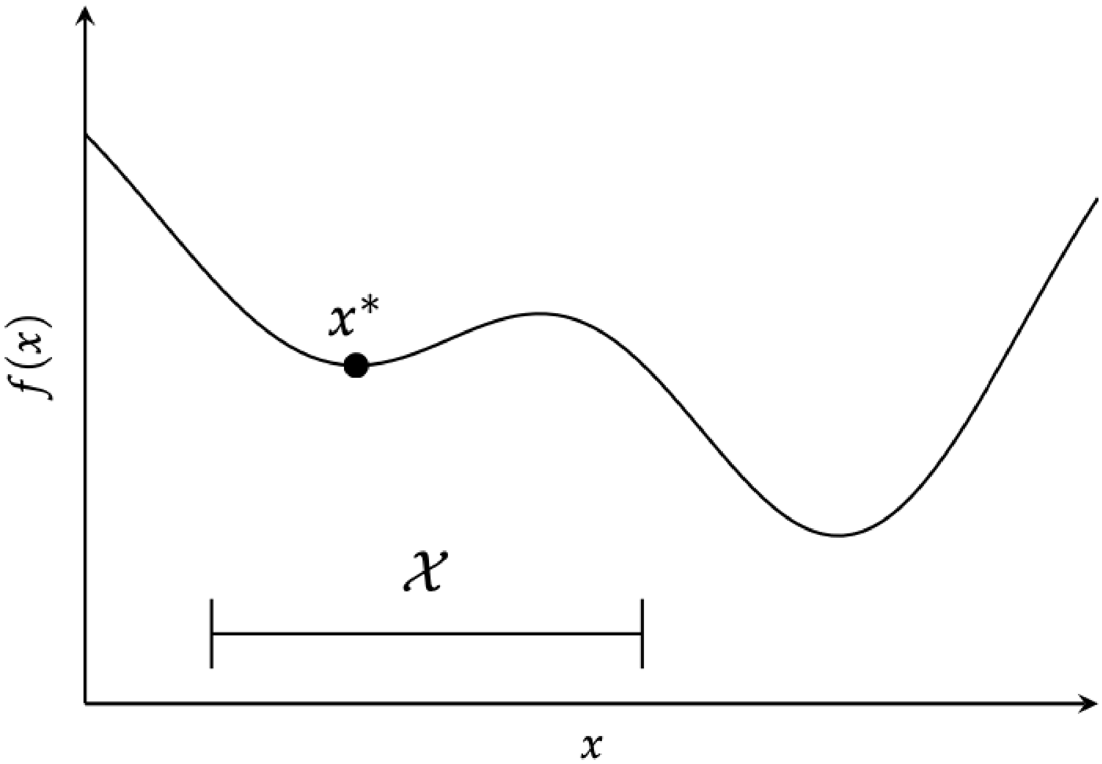
where x_n refers to the n-th *design variable*.

So, a basic optimization problem with an objective function f is written as the following:

$$\begin{aligned} \underset{\mathbf{x} \in \mathcal{X}}{\text{minimize}} \quad & f(\mathbf{x}) \\ \text{subject to} \quad & g_i(\mathbf{x}) \leq 0, \quad \forall i \in \{1, \cdots, \ell\} \end{aligned}$$

where ℓ is the number of constraints. Since the design point is often a vector, constraints are applied element-wise. We should note that since constraints limit the feasible domain, it is possible that the optimal solution $\mathbf{x}^*$ is not the global minimum or maximum solution, as can be seen in Figure 2.1 (Kochenderfer and Wheeler 2019, fig. 1.3).

Figure 2.1: Global Extrema Outside Feasible Set



2.2.2 Multiobjective Optimization Problem

Suppose we are interested in $k \geq 2$ objectives and we seek to simultaneously optimize all of them. We define each objective as the following:

$$f_i : \mathcal{X} \to \mathbb{R} \qquad \text{for } i = 1, \cdots, k \text{ and where } k \geq 2.$$

In other words, our objective function $\mathbf{f} : \mathcal{X} \to \mathbb{R}^k$ can be written as

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} f_1(\mathbf{x}) & f_2(\mathbf{x}) & \cdots & f_k(\mathbf{x}) \end{bmatrix}^T,$$

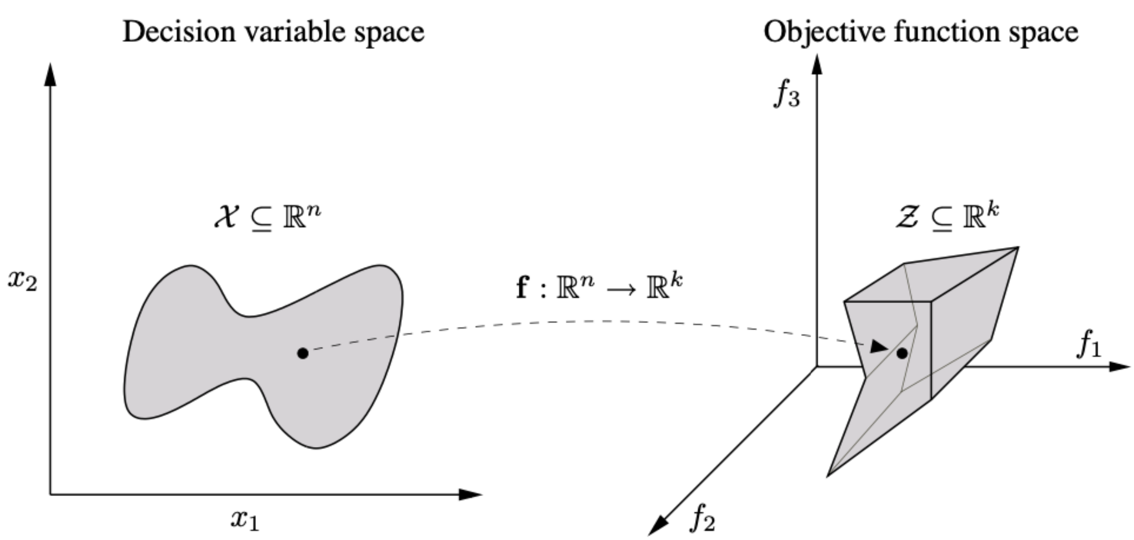
where $\mathbf{x} \in \mathcal{X}$ is a design point. We wish to find the optimal solution $\mathbf{x}^* \in \mathcal{X}$ that would satisfy the following:

$$\begin{aligned} \underset{\mathbf{x} \in \mathcal{X}}{\text{minimize}} \quad & \mathbf{f}(\mathbf{x}) \\ \text{subject to} \quad & g_i(\mathbf{x}) \leq 0, \quad \forall i \in \{1, \cdots, \ell\} \end{aligned}$$

where ℓ is the number of constraints.

The *decision variable space* is the set of all possible design variables values. Likewise, the *objective function space* is the set of all possible values of each objective function. For a design point of length $n = 2$ and a vector function of length $k = 3$, the visual representation can be seen in Figure 2.2, where $\mathcal{Z}$ is the image of $\mathcal{X}$ under $\mathbf{f}$ (Jaimes, Zapotecas-Martínez, and Coello 2011, fig. 1).

Figure 2.2: Decision Variable and Objective Function Space



In single objective optimizations (i.e., $k = 1$), two solutions $\mathbf{x}$ and $\mathbf{x}'$ can be ranked objectively by their scalar values. For example, if we wish to minimize f and $f(\mathbf{x}) = 18$ and $f(\mathbf{x}') = 17$, then $\mathbf{x}'$ is an objectively better solution than

$\mathbf{x}$. However, in multiobjective optimization problems, there is no canonical way of ranking solutions as there are $k \geq 2$ dimensions to consider simultaneously. The common methodology adopted to navigate this issue is called the *Pareto dominance relation*.

We say $\mathbf{x}$ is an objectively better solution than $\mathbf{x}'$, that is $\mathbf{x}$ *dominates* $\mathbf{x}'$, if both of the following conditions hold:

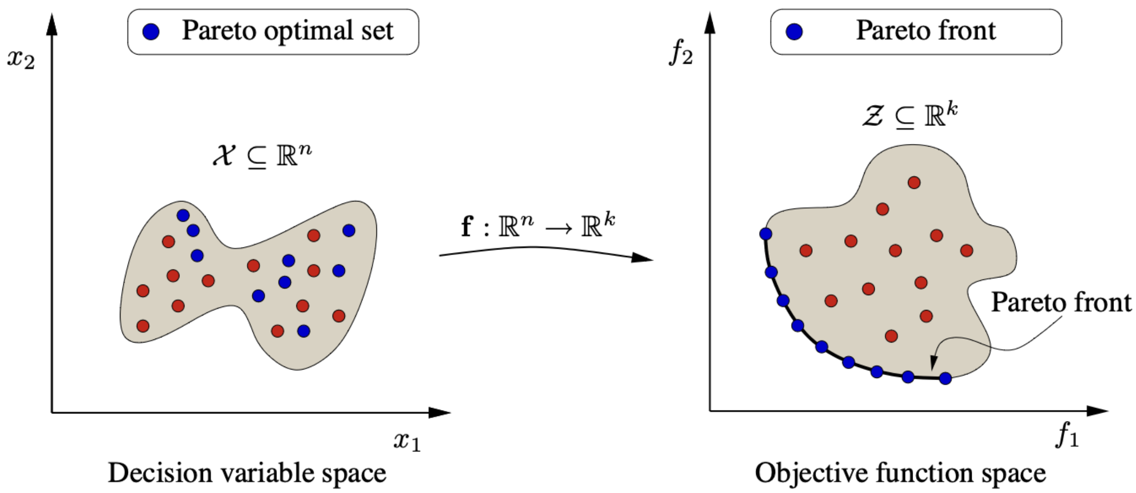
$$\begin{aligned} f_i(\mathbf{x}) &\leq f_i(\mathbf{x}') \quad \forall i \in \{1, \cdots, k\}, \\ f_i(\mathbf{x}) &< f_i(\mathbf{x}') \quad \exists i \in \{1, \cdots, k\}. \end{aligned} \tag{2.5}$$

If only the first condition holds, then we say $\mathbf{x}$ *weakly dominates* $\mathbf{x}'$. Similarly, we define $\mathbf{x}$ as non-dominated if:

$$\nexists \mathbf{x}' \in \mathcal{X} \text{ where } \mathbf{x}' \text{ dominates } \mathbf{x}. \tag{2.6}$$

A non-dominated solution is also called a Pareto optimal solution, and the set of all such solutions is denoted by $\mathcal{P}^*$. The image of this set under the vector function $\mathbf{f}$ is a set called the *Pareto Frontier* or *Pareto Front*, denoted as $\mathcal{PF}^*$. A visual representation of these two concepts can be seen in Figure 2.3 where $\mathcal{Z}$ is the image of $\mathcal{X}$ under $\mathbf{f}$ (Jaimes, Zapotecas-Martínez, and Coello 2011, fig. 3).

Figure 2.3: Pareto Optimal Solutions and Pareto Front in Decision Variable and Objective Function Spaces



Genetic Algorithm

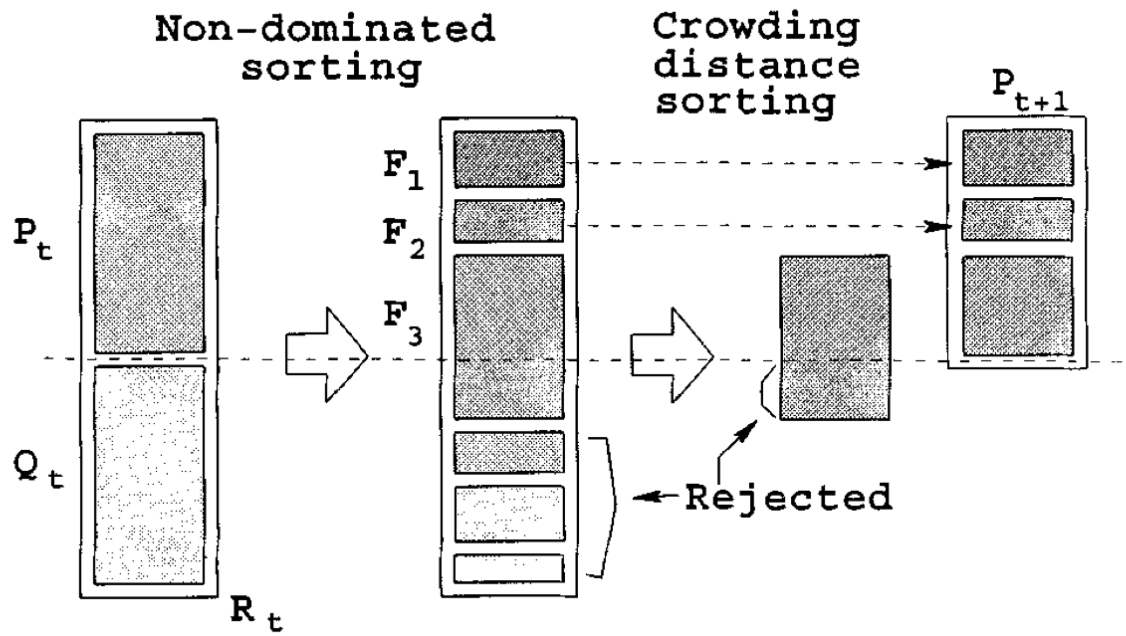
In general, algorithms employed to solve optimization problems are designed to converge to the global minimum. The faster they converge, the better they are. In single objective optimization problems, there exist a variety of approaches such as calculus-based approaches and linear programming. However, these techniques alone are not suitable for multiobjective optimization.

The ways of solving multiobjective optimization problems can be divided into two categories: scalarization approaches and Pareto approaches (Weck 2004). Scalarization approaches simply translate the multiobjective optimization problem into one or more single objective optimization problems. However, these approaches often result in a less complete objective function space with many missing Pareto solutions. Pareto approaches often utilize the concept of Pareto dominance relations to solve problems.

Pareto approaches use evolutionary algorithms (EAs), which are population-based approaches inspired by biology. The most common type of EAs are genetic algorithms (GAs), which are inspired by genetics (Eiben and J. Smith 2015). Typically, GAs work by first initializing a population of solutions. Each solution is called a chromosome and is usually represented as a binary string of fixed length. Each entry of the chromosome is called a gene. The solutions are ranked based on their performance in the objective function space. The better a solution is, the more likely it will be chosen as a parent solution. After all parent solutions are chosen, some undergo a mutation operation while others undergo a crossover, or recombination. The resulting solutions are the child solutions and they replace their parents in the population. The process is repeated until a sufficient child solution is found. In the 1990s, a breakthrough was made on how GAs can converge faster if they utilized an elitist strategy—when you assure the highest performing solutions of every generation are inserted into the next (Eiben and J. Smith 2015).

The most popular type of GA is the Non-dominated Sorting Genetic Algorithm II, or NSGA-II (Deb et al. 2002). Like the name indicates, it uses non-dominated sorting to rank solutions in the population and hence is ideal for multiobjective optimization problems. Additionally this algorithms employs elitism for faster convergence and a method knows as crowding distance to preserve diversity among the population. The notion of Pareto dominance is emphasized in this algorithm. We can essentially describe NSGA-II to be converging to the true Pareto Frontier by finding the frontier at every generation. In this analysis, we use NSGA-II to perform multiobjective optimization. Figure 2.4 (Deb et al. 2002, fig. 2) provides a general visualization of the process of this algorithm.

Figure 2.4: NSGA-II Procedure



2.3 Optimizing Country-Level Water Usage

In this section, we formally set up the water usage of a target nation T in a specific year Y as an optimization problem. Our goal is to decrease water usage while increasing revenue relative to a set of agricultural commodities C. We know the production and trade of these commodities also impacts revenue. While maximizing water usage would lead to maximizing revenue, a water-scarce nation may not be able to afford high water usage, and hence it becomes an interesting problem to find the best set of trade-offs in water usage and revenue. We use the following information from the year Y to calculate the *baseline* values of water usage (W) and revenue (R) associated with nation T for the commodities C:

- relevant weather and crop data to calculate the water footprint of each commodity,

- for each commodity, the quantity that was domestically produced, the yield, and the domestic revenue rate at which each commodity is sold,
- the import/export quantity and revenue rate matrices containing information about the quantity and the revenue rate of each commodity from every trading nation.

To solve the optimization problem, we want to find solutions that (1) yield a water usage value less than or equal to W and (2) yield a revenue value greater than or equal to R. In other words, we want to avoid results that are trivially optimal (i.e. a low water usage at the expense of a low revenue, relative to baseline values). To do so, we add constraints to *limit water usage* and *maximize revenue* relative to the baseline values W and R, respectively.

The reason the nation T is producing and trading C is because there is a need or demand for C, whether that be for economical or other societal reasons. We define the baseline domestic demand for C in the given year as aggregate domestic production plus aggregate imports minus aggregate exports (i.e., production + imports − exports). We define a *reliable supply* constraint to assure that any potential solution has a domestic demand value that is greater than or equal to the baseline domestic demand value. If such a solution exists, then we say reliable supply is met for that solution.

While the way the optimization problem is currently set up prevents the country T from being completely dependent on imports to meets its domestic demand, a high dependence on imports is still possible. In the context of agricultural commodities, T being highly dependent on other nations to feed its citizens can be dangerous. We define a *food security* constraint to assure that any potential solution has an aggregate domestic production value that is greater than or equal to a *quarter* of the aggregate domestic demand value, or 25% food security (Scenario A). If such a solution exists, then we say food security is met for that solution. Additionally, we consider another scenario where the aggregate domestic production value is constrained to be greater than or equal to *half* of the aggregate domestic demand value, or 50% food security (Scenario B).

To reiterate, we want to optimize the production, import, and export quantities of C for the year Y. In our analysis, we optimize trade at the nation level, meaning for each nation that engaged in trade with T, the quantity that was traded is considered when finding optimal solutions.

Now, it is entirely possible that if T had produced and traded more than what they did in the baseline year Y that they could generate more revenue and use less water usage. However, in terms of optimization, we need to know what the upper bounds of quantity values for each commodity in terms of production, import, and export. Without knowing more information about the capabilities and infrastructure of T, we cannot accurately determine what the upper bounds are. If T produced 1000 tonnes of wheat in the baseline year, we cannot say T should produce 1100 tonnes of wheat instead without knowing more information; T might have just only have had enough land to produce 1000 tonnes of wheat. The same can be applied to import and export quantity values. As a result, we define the upper bound to be equal to the corresponding quantity value from the baseline year. So, in the context of the scenario above, the design variable associated with the production of wheat can only have a value between 0 and 1000, inclusively.

Mathematically, suppose there are n distinct commodities and m distinct nations involved in the trade of the commodities with the target nation T. Not every nation that T imported from will also be exported to, but for purposes of outlining the design of the problem, we will assume this symmetry exists and later address this assumption. Therefore, our feasible domain $\mathcal{X}$ has $n + 2(m \cdot n)$ dimensions, or

$\mathcal{X} \subseteq \mathbb{R}^{n+2(m \cdot n)}$. This becomes clear after seeing what a design point looks like in the next paragraph. Since we have 2 objective functions and both can have negative and positive values, we define them as the following:

$$f_i : \mathcal{X} \to \mathbb{R} \qquad \text{for } i = 1, 2, \tag{2.7}$$

where f_1 measures water usage and f_2 measures revenue. We then define our vector function $\mathbf{f}$ as the following:

$$\mathbf{f} : \mathcal{X} \to \mathbb{R}^2. \tag{2.8}$$

We can explicitly write $\mathbf{f}$ as the following column vector:

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} f_1(\mathbf{x}) & f_2(\mathbf{x}) \end{bmatrix}^T. \tag{2.9}$$

The design point $\mathbf{x}$ can be expressed as

$$\mathbf{x} = \begin{bmatrix} \overrightarrow{PQ} & \overrightarrow{IQ} & \overrightarrow{EQ} \end{bmatrix}^T, \tag{2.10}$$

where $\overrightarrow{PQ}$, $\overrightarrow{IQ}$, and $\overrightarrow{EQ}$ represent the domestic production quantity (dimension n), import quantity (dimension $m \times n$), and export quantity (dimension $m \times n$), respectively.

In its entirety, our optimization problem is as follows:

$$\begin{aligned} \underset{\mathbf{x} \in \mathcal{X}}{\text{minimize}} \quad & \mathbf{f}(\mathbf{x}) = \begin{bmatrix} f_1(\mathbf{x}) & f_2(\mathbf{x}) \end{bmatrix}^T \\ \text{subject to} \quad & g_1(\mathbf{x}) \geq 0, \quad \text{(Reliable Supply)}, \\ & g_2(\mathbf{x}) \geq R, \quad \text{(Maximize Revenue)}, \\ & g_3(\mathbf{x}) \geq 0, \quad \text{(Food Security)}, \\ & g_4(\mathbf{x}) \leq W, \quad \text{(Limit Water Use)}. \end{aligned} \tag{2.11}$$

The objective and constraint functions are fully described in the following sections.

2.3.1 First Objective

The first objective is to minimize the water usage of our set of n commodities. Suppose WF is a $n-$vector that represents the water footprint associated with each of the commodities (in $\frac{\text{m}^3}{\text{tonne}}$), and $\overrightarrow{EQ_j}$ ($\overrightarrow{IQ_j}$) is a $n-$vector that measures the export (import) quantity of the n commodities to the nation j, we can mathematically express our first objective as follows:

$$f_1(\mathbf{x}) = \overrightarrow{WF} \cdot \overrightarrow{PQ} + \sum_{j=1}^{m} \overrightarrow{WF} \cdot (\overrightarrow{EQ_j} - \overrightarrow{IQ_j}). \tag{2.12}$$

We minimize this objective function subject to the following three constraints.

- Reliable Supply:

$$g_1(\mathbf{x}) = \overrightarrow{PQ} \cdot \overrightarrow{1} + \sum_{j=1}^{m} (\overrightarrow{IQ_j} - \overrightarrow{EQ_j}) \cdot \overrightarrow{1} - \overrightarrow{DD} \cdot \overrightarrow{1} \geq 0, \tag{2.13}$$

where $\overrightarrow{DD}$ is the baseline domestic demand quantity vector of length n (in units of tonne). We calculate domestic demand as

$$\overrightarrow{DD} = \overrightarrow{PQ} + \sum_{j=1}^{m} (\overrightarrow{IQ_j} - \overrightarrow{EQ_j}). \tag{2.14}$$

- Maximize Revenue:

$$g_2(\mathbf{x}) = \overrightarrow{RP} \cdot \overrightarrow{PQ} + \sum_{j=1}^{m} \overrightarrow{NR_j} \cdot \overrightarrow{1} \geq R, \tag{2.15}$$

  where $\overrightarrow{RP}$ (dimension n) represents the domestic production revenue rate of the n commodities $(\frac{\text{USD}}{\text{tonne}})$, $\overrightarrow{NR_j}$ (dimension n) represents the net revenue of trading with nation j, and R is the net revenue in USD relative to the selected commodities from the baseline year. The net revenue $\overrightarrow{NR_j}$ is calculated based on the import and export revenue rates, denoted by $\overrightarrow{RI_j}$ and $\overrightarrow{RE_j}$, as

$$\overrightarrow{NR_j} = \overrightarrow{RE_j} \cdot \overrightarrow{EQ_j} - \overrightarrow{RI_j} \cdot \overrightarrow{IQ_j}.$$

- Food Security:

$$g_3(\mathbf{x}) = \overrightarrow{PQ} \cdot \overrightarrow{1} - \frac{\overrightarrow{DD} \cdot \overrightarrow{1}}{4} \geq 0. \tag{2.16}$$

  This constraint ensures that a quarter of all aggregate baseline domestic demand is to be met through domestic production.

2.3.2 Second Objective

The second objective function is concerned with maximizing the net revenue, written as:

$$f_2(\mathbf{x}) = -g_2(\mathbf{x}) = -\overrightarrow{RP} \cdot \overrightarrow{PQ} - \sum_{j=1}^{m} \overrightarrow{NR_j} \cdot \overrightarrow{1}. \tag{2.17}$$

Note that we negate the value so we can computationally treat it as a minimization, instead of a maximization problem. This objective function is subject to the following constraint.

- Limit Water Use:

$$g_4(\mathbf{x}) = f_1(\mathbf{x}) = \overrightarrow{WF} \cdot \overrightarrow{PQ} + \sum_{j=1}^{m} \overrightarrow{WF} \cdot (\overrightarrow{EQ_j} - \overrightarrow{IQ_j}) \leq W, \tag{2.18}$$

  where W denotes the total agricultural water usage relative to the selected commodities for the baseline year in m^3.

2.4 A Numeric Example

In this section, we provide a numeric example to demonstrate our methodology. Suppose we are interested in optimizing the production and trade quantities of $n = 3$ commodities (apples, bananas, and oranges) for a target nation that trade with $m = 3$ foreign nations. Numeric values used for this calculation are provided below.[1]

[1] Note that these values are fabricated for demonstration purposes and according to economic theory, any country will (mostly) either be an importer or exporter of any commodity, not both.

Table 2.1: Relevant Values for Example Problem

Total Water Footprint ($\frac{\text{m}^3}{\text{tonne}}$)		
Apple	Banana	Orange
10,000	900	200

Domestic Production Quantity (tonne)		
Apple	Banana	Orange
100	400	500

Import Quantity (tonne)			
	Apple	Banana	Orange
Nation A	50	10	14
Nation B	80	40	29
Nation C	50	60	43

Export Quantity (tonne)			
	Apple	Banana	Orange
Nation A	10	20	20
Nation B	30	70	100
Nation C	50	60	80

Domestic Demand (tonne)		
Apple	Banana	Orange
190	360	386

Domestic Rate ($\frac{\text{USD}}{\text{tonne}}$)		
Apple	Banana	Orange
350	230	90

Import Rate ($\frac{\text{USD}}{\text{tonne}}$)			
	Apple	Banana	Orange
Nation A	300	230	100
Nation B	250	100	140
Nation C	200	240	180

Export Rate ($\frac{\text{USD}}{\text{tonne}}$)			
	Apple	Banana	Orange
Nation A	200	310	90
Nation B	90	230	150
Nation C	190	160	20

In this scenario, apple is an extremely water intensive crop, has the smallest domestic production value but with the largest domestic revenue rate, and generally has the largest import revenue rates. Conversely, orange is the least water expensive crop, has the largest domestic production but with the smallest domestic revenue rate, and generally has the largest export revenue rates. Intuitively, producing apples is not ideal in terms of water usage, but they can also generate large amounts of revenue. However, when considered with the rest of the commodities, the solution is not obvious. We want to show just how powerful multiobjective optimization is in these types of problems.

Note that the exact quantities of production, import, and export are not as relevant for this problem as knowing their ratios and composition by item and type. We use pie donut charts to visualize the proportions associated with baseline value calculations, as shown in Figure 2.5a and Figure 2.5b.

With the vector notation, data can be expressed as the following:

$$\begin{aligned}
\overrightarrow{WF} &= \begin{bmatrix} 10000 & 900 & 200 \end{bmatrix}, & \overrightarrow{PQ} &= \begin{bmatrix} 100 & 400 & 500 \end{bmatrix}, \\
\overrightarrow{IQ} &= \begin{bmatrix} 50 & 10 & 14 \\ 80 & 40 & 29 \\ 50 & 60 & 43 \end{bmatrix}, & \overrightarrow{EQ} &= \begin{bmatrix} 10 & 20 & 20 \\ 30 & 70 & 100 \\ 50 & 60 & 80 \end{bmatrix}, \\
\overrightarrow{DD} &= \begin{bmatrix} 190 & 360 & 386 \end{bmatrix}, & \overrightarrow{RP} &= \begin{bmatrix} 350 & 230 & 90 \end{bmatrix}, \\
\overrightarrow{RI} &= \begin{bmatrix} 300 & 230 & 100 \\ 250 & 100 & 140 \\ 200 & 240 & 180 \end{bmatrix}, & \overrightarrow{RE} &= \begin{bmatrix} 200 & 310 & 90 \\ 90 & 230 & 150 \\ 190 & 160 & 20 \end{bmatrix}.
\end{aligned} \tag{2.19}$$

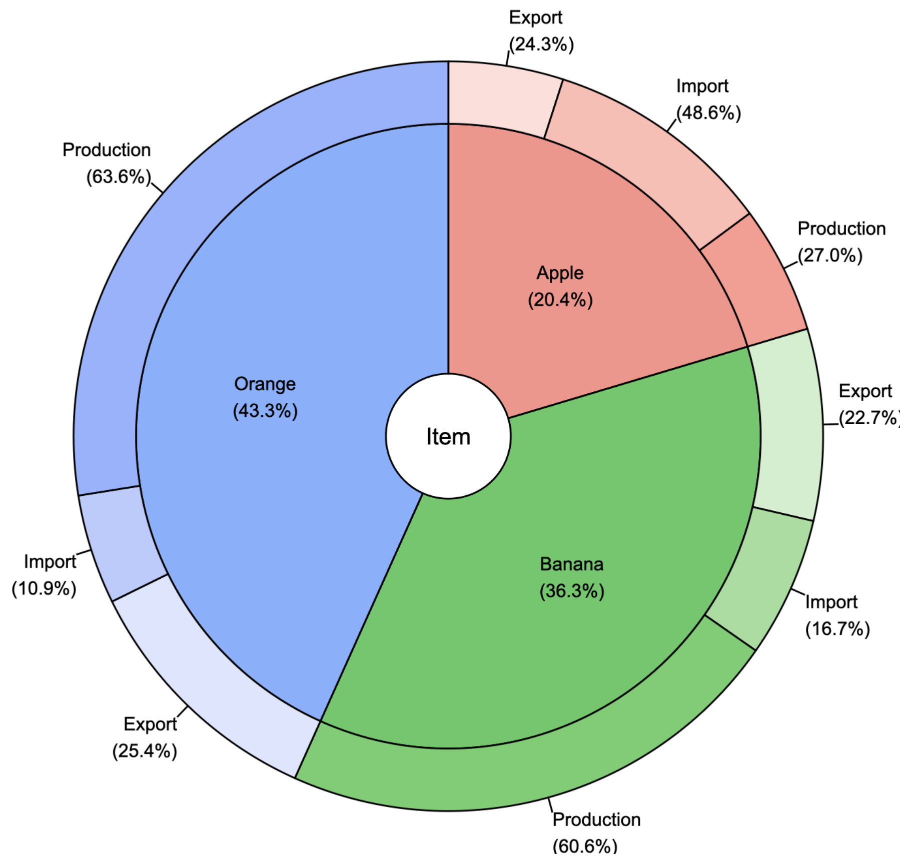
To clarify, $\overrightarrow{IQ}$ is written as the column vectors $\begin{bmatrix} IQ_1 & IQ_2 & IQ_3 \end{bmatrix}$, and $\overrightarrow{EQ}$, $\overrightarrow{RI}$, $\overrightarrow{RE}$ are written in the same fashion. Using the above, we can calculate the baseline values:

$$\mathbf{f}(\overrightarrow{X}) = \begin{bmatrix} f_1(\overrightarrow{X}) & f_2(\overrightarrow{X}) \end{bmatrix}^T = \begin{bmatrix} 618800 & -157600 \end{bmatrix}^T. \tag{2.20}$$

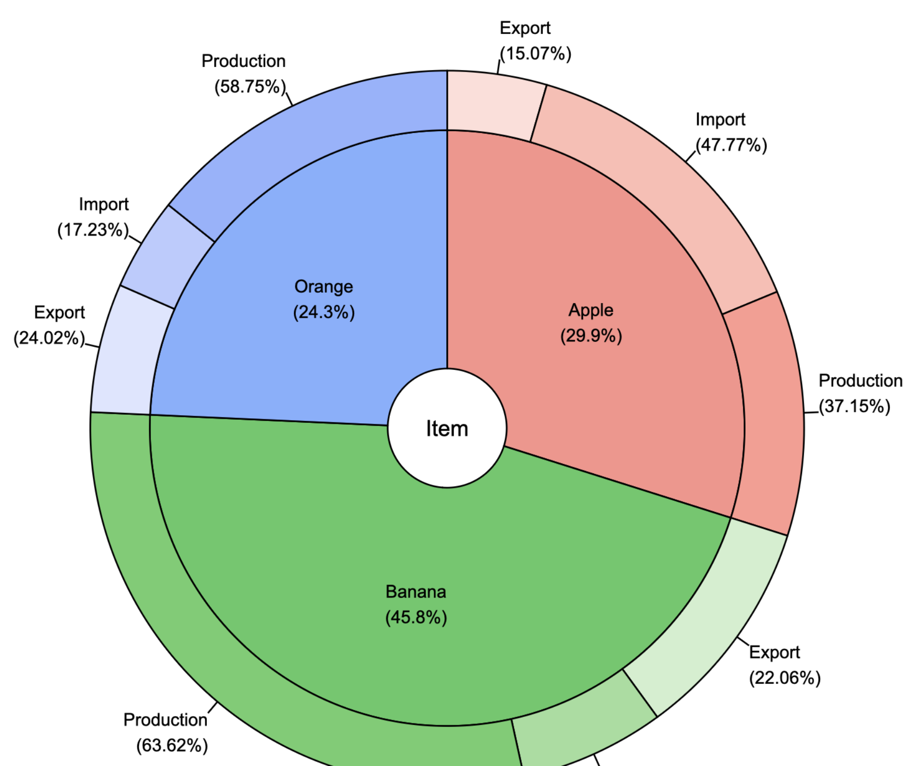
Intuitively, our target nation used approximately $618,800$ m^3 of water in the form of apples, bananas, and oranges. These crops also contributed to $157,600$ USD to the GDP. Our goal is to find production, import, export quantities for the three crops, so that the GDP contribution is greater than $157,600$ USD and water usage is less than $618,800$ m^3. In this setup, the parameter space has dimension $3 + 2 \times (3 \cdot 3) = 21$.

Figure 2.5: Distribution of Production, Import, and Export Values for Example Problem

(a) Quantity Distribution



(b) Revenue Distribution

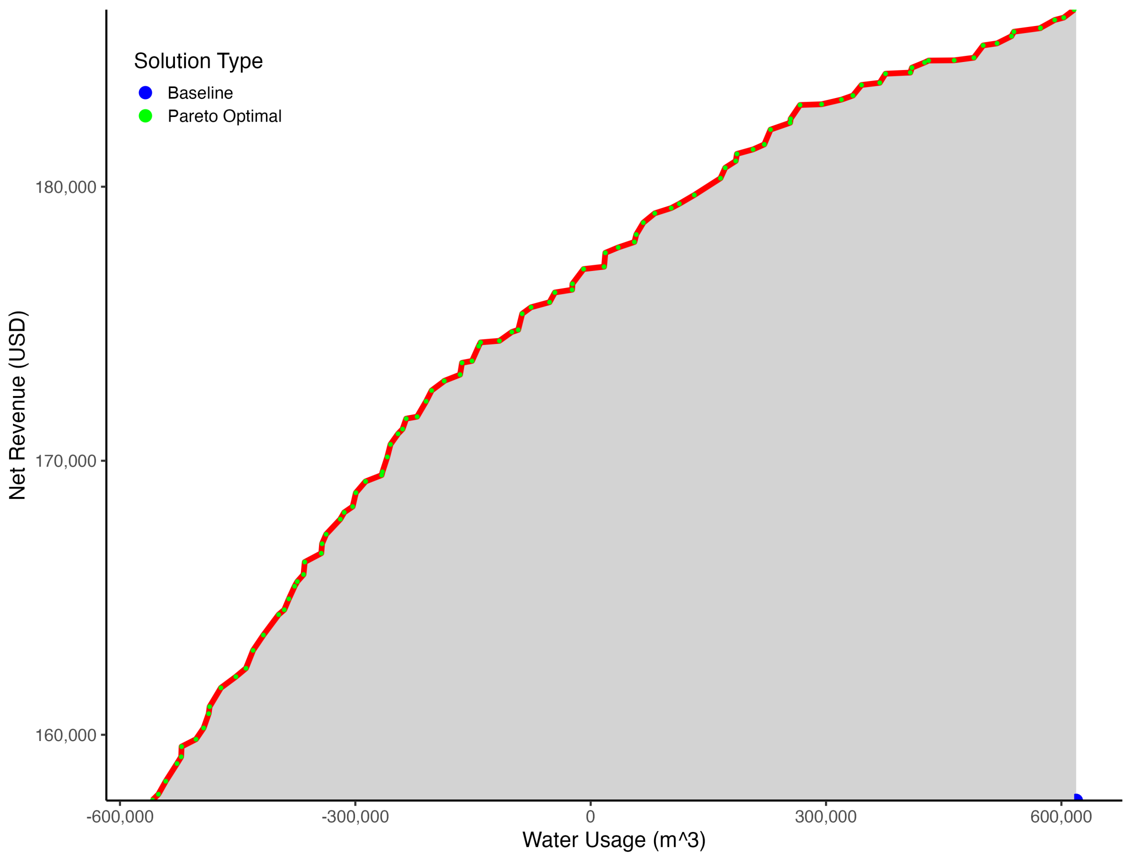


2.4.1 Optimization Results

We use our model to optimize for the example presented above using the R *mco* package (Mersmann 2020). We ran the NSGA-II algorithm for our vector objective function containing 2 objectives and 4 constraints for 1000 generations with a population size of 100. The crossover probability and distribution index was kept at the defaults of 0.7 and 5, respectively. The mutation probability and distribution index was kept at the defaults of 0.2 and 10, respectively. Out of 100 solutions, 100 were Pareto optimal. We only kept Pareto optimal solutions in the following discussion.

In Figure 2.6 we show the objective function space. The red line indicates the Pareto Frontier and the green points on the line are the 100 solutions the algorithm found. The gray area shaded below the frontier indicates the region where the dominated solutions are. The blue point, located in the bottom right corner, is the baseline value.

Figure 2.6: Objective Function Space of Example Problem

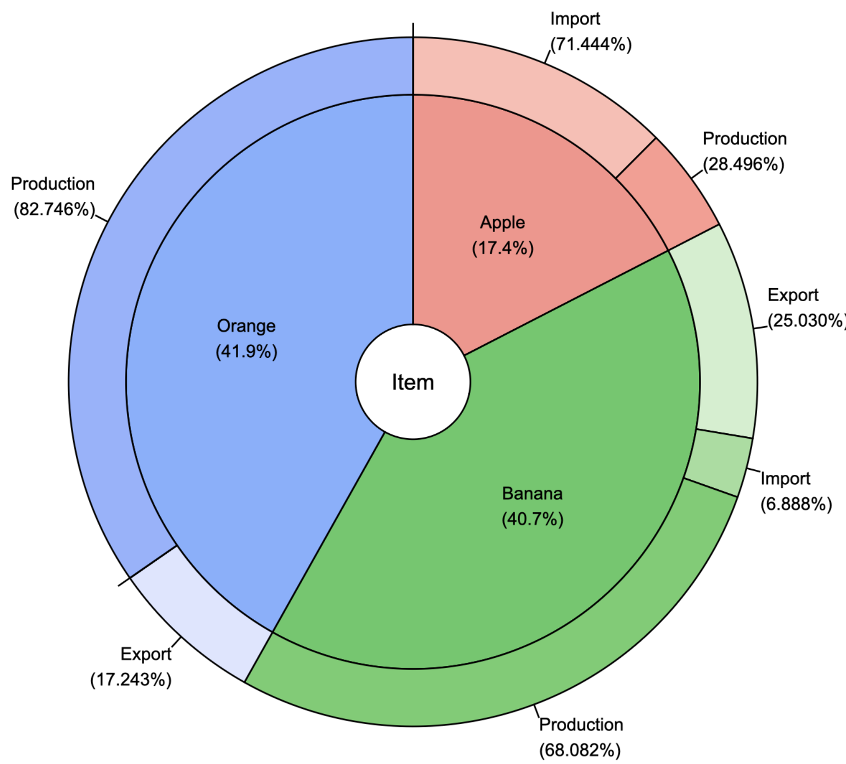


We can randomly pick one solution and visualize the quantity and revenue distributions associated with the particular design variables in Figures 2.7a and 2.7b.[2] This particular solution utilized approximately $-503,129$ m^3 of water while also generating $159,837$ USD in revenue. The negative value indicates the nation saved water.

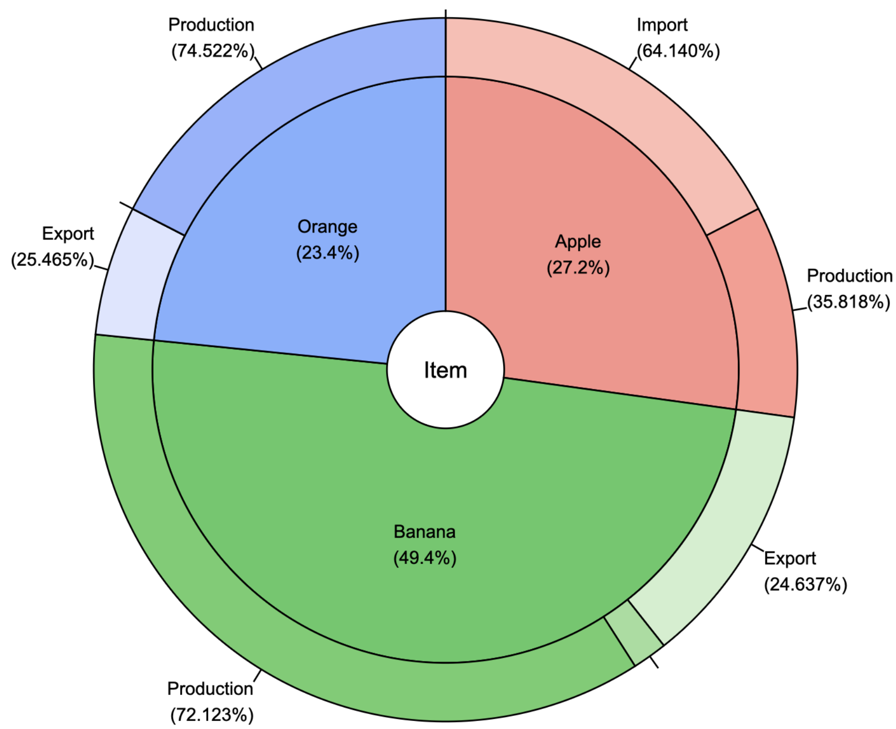
[2]Some parts of the donut are not labeled due to percentages being close to 0.

Figure 2.7: Distribution of Production, Import, and Export Values of a Random Solution from Example Problem

(a) Quantity Distribution



(b) Revenue Distribution



Chapter 3

Data and Results

3.1 Data

We perform this analysis on the Hashemite Kingdom of Jordan for the year 2019. Climate, economic, and crop data are obtained from various resources. Specifically, we used the *riem* and *weathermetrics* packages in R for the climate data and used the *SPEI* package for calculating crop evapotranspiration, or ET_c (Salmon 2022; Anderson, Peng, and Ferreri 2016; Beguería and Vicente-Serrano 2023). Additionally, we relied on the *FAOSTAT* package to fetch data from FAOSTAT (J. et al. 2023). Details of data used in the analysis are given in the following sections.

3.1.1 Climate Data

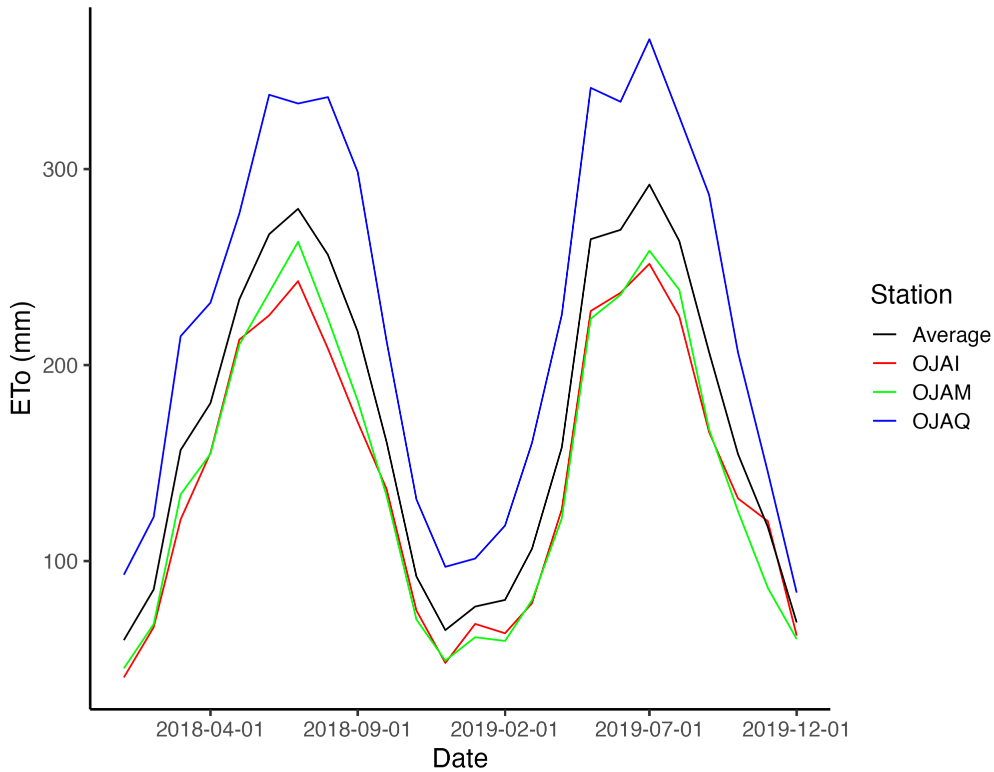
The majority of the necessary climate data was collected from historical Meteorological Aerodrome Report, or METAR, a standard protocol used in aviation to communicate weather conditions. The weather information encoded via the protocol varies. The Iowa Environmental Mesonet (IEM) has archived data of METAR reports for all 3 Jordan airports since January 7th, 2000 (Iowa State University 2024).

We collected hourly interval data from January 1st, 2018 to December 31st, 2019 of the following variables for each station: longitude, latitude, altitude, temperature, dewpoint temperature, relative humidity, and wind speed.

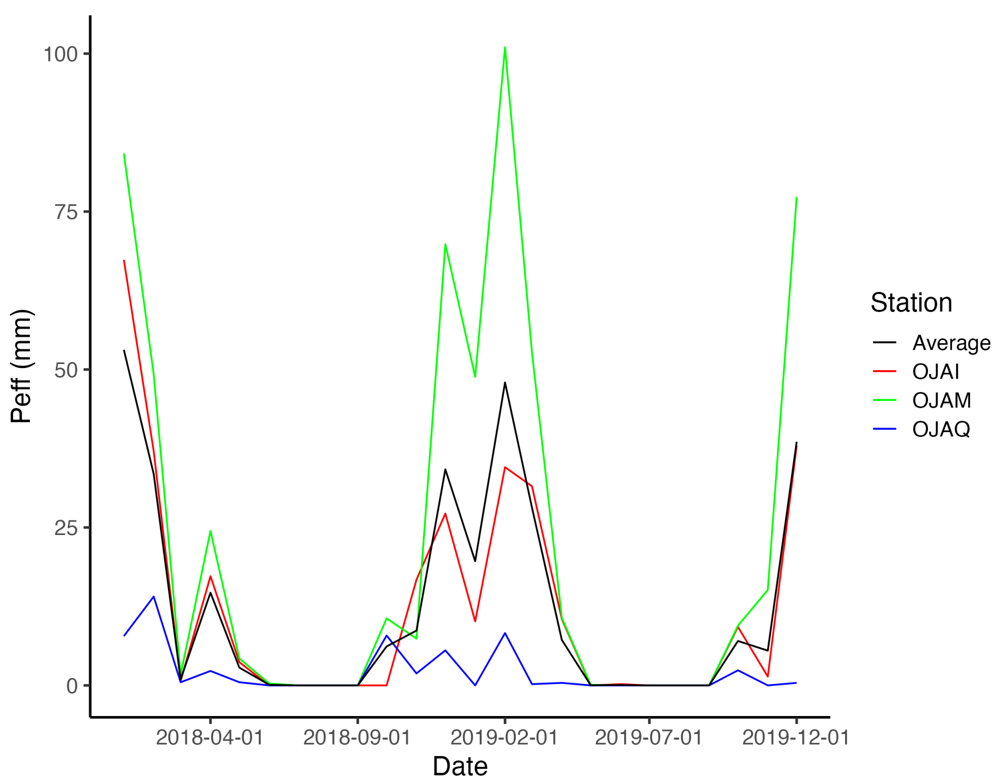
We converted the measurements in the standard format that the FAO P-M equation requires. We first aggregated the measurements and computed the daily average of each variable listed above for each station, respectively. We then repeated the process to compute the monthly average values. The missing variables, namely hours of sunshine and precipitation, were purchased from the Jordan Meteorological Department as monthly average values. For each station and every month in the 2 year span, we calculated the ET_o and P_{eff}. Finally, we grouped by each month of every year across all stations to calculate the average monthly ET_o and P_{eff}. In Figures 3.1a and 3.1b we visualize the ET_o and P_{eff} across each station as well as the monthly average values of both variables, respectively. The data is reflective of typical climate in Jordan with the cooler months being from September to March, which is commensurate with cropping patterns.

Figure 3.1: ET_o and P_{eff} Across Time

(a) ET_o

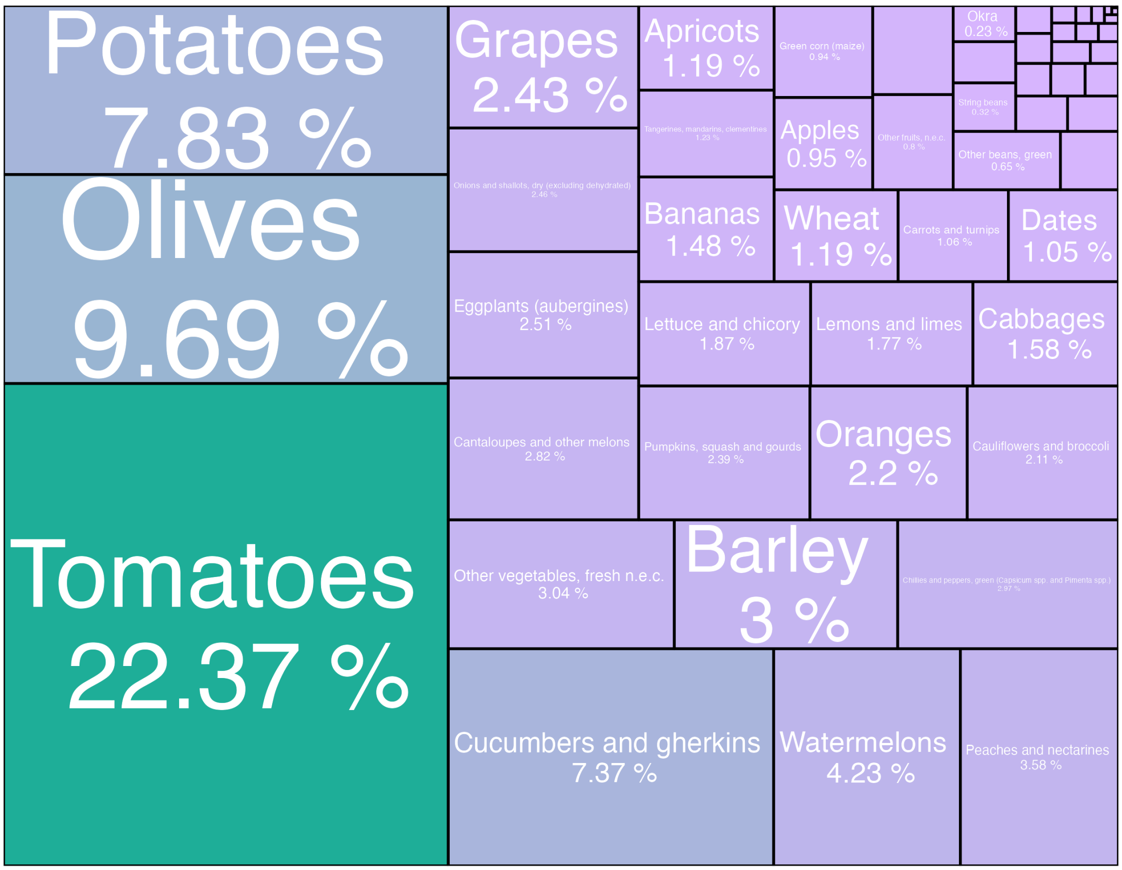


(b) P_{eff}



3.1.2 Economic Data

Figure 3.2: Agricultural Commodities Ranked by Domestic Production in 2019



We primarily used FAOSTAT to collect the following economic data.

- Production - Crop and Livestock Products (QCL): to obtain information like the production quantity and yields for a set of agricultural commodities during a given year.
- Prices - Producer Prices (PP): to obtain the revenue rates at which a set of agricultural commodities were sold domestically during a given year.
- Trade - Detailed Trade Matrix (TM): to obtain the quantities and revenue rates for a set of agricultural commodities that were imported to and exported

from Jordan during a given year, as well as nations that were involved in trade of a set of agricultural commodities during a given year.

A transformation of the TM database was applied to create more symmetric calculations. In summary, we created complete import quantity and revenue matrices by also including nations that Jordan exported to but not imported from. These values were inserted as 0 in both the quantity and revenue matrices. We did something similar to a create complete export quantity and revenue matrices.

Data from QCL was needed to calculate the water footprint values while data from PP and TM were for baseline value calculations. Data from QCL and TM was also used to determine the upper boundaries of the design elements (quantities of production, import, and export for each commodity). We should note that some values from QCL were blank for certain attributes, like yield for maize. In such cases we assumed the yield value to be 1.

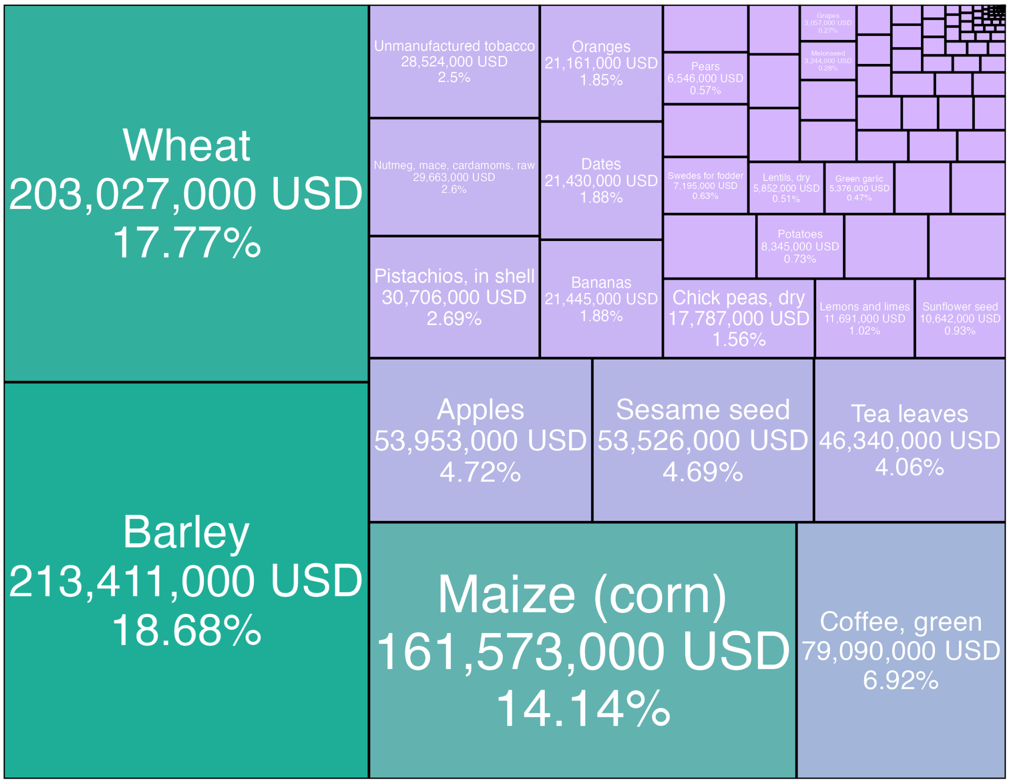
FAOSTAT reports the the description or type of commodities traded using the Central Product Classification (CPC) Version 2.1 scheme (United Nations 2015). We filtered for commodities in Division 01: Products of Agriculture, Horticulture and Market Gardening in Section 0: Agriculture, Forestry, and Fishery Product. As a result, we excluded certain other valuable trade commodities like rice and sheep.[1] We refer to this list of commodities as the set of agricultural commodities.

To determine which crops to select, we consider the domestic production quantity (in tonnes) and trade value (in USD) of these commodities. Using the data from QCL, we visualize the agricultural commodities by the proportion of units (in tonnes) produced in 2019, in Figure 3.2. Using the data from TM, we visualize the aggregated total trade values of the agricultural commodities in Figures 3.3a

[1]While rice is technically listed under this section, milled rice is what is actually relevant and falls under Section 2.

Figure 3.3: Agricultural Commodities Ranked by Aggregated Trade Value in 2019

(a) Imports



(b) Exports

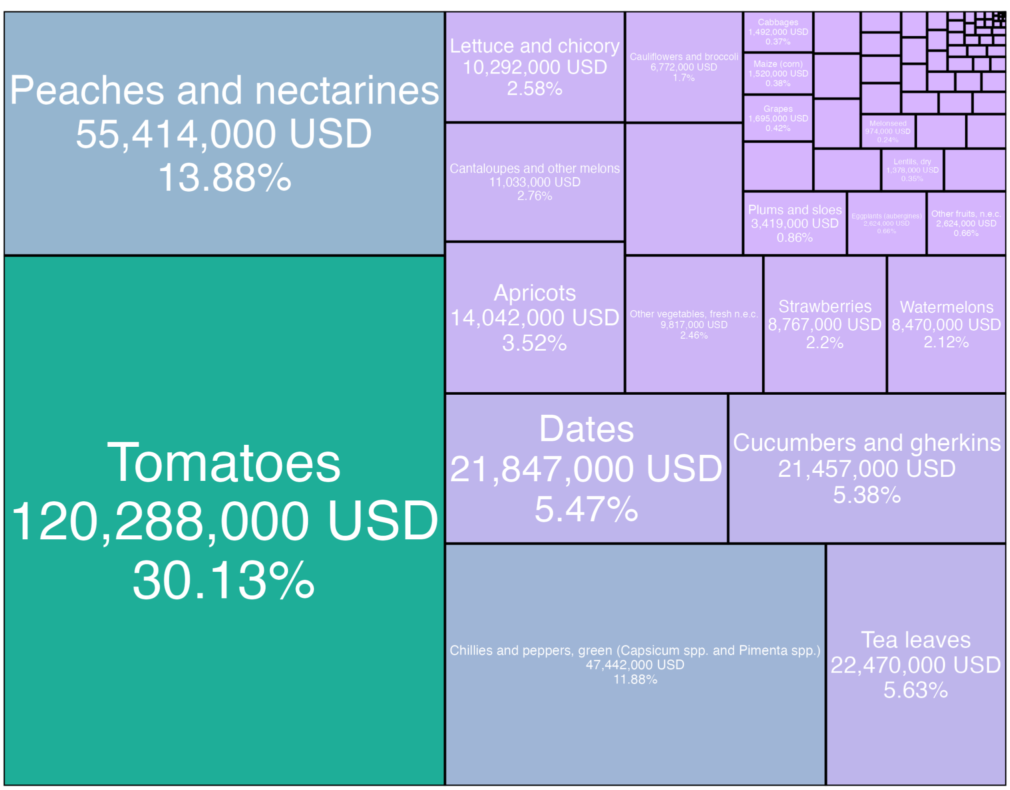
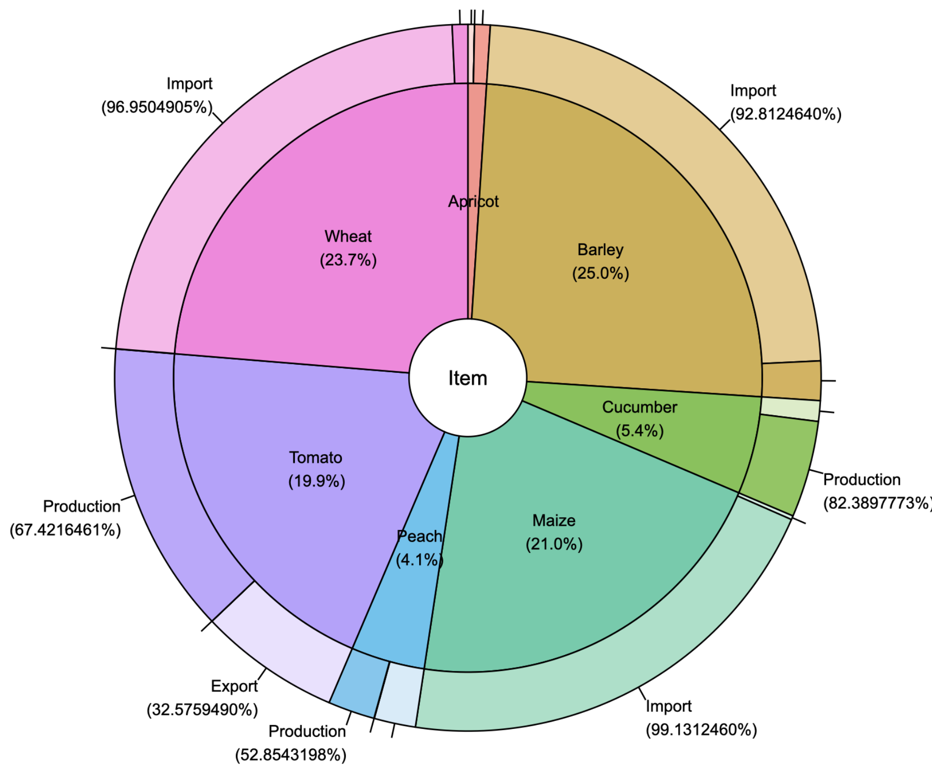
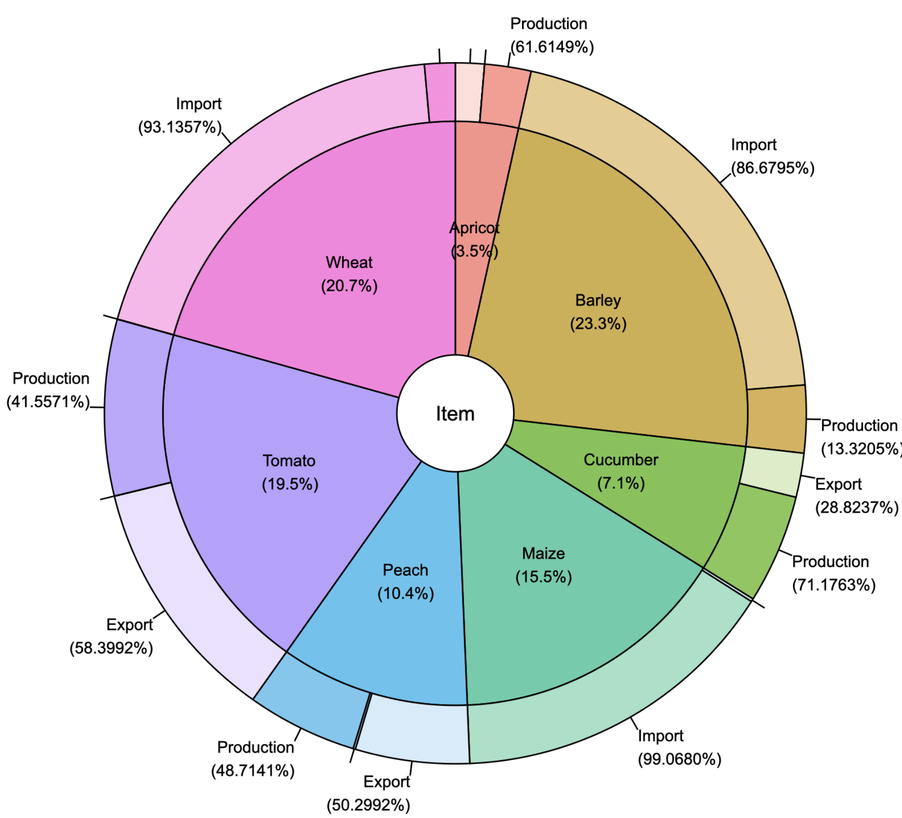


Figure 3.4: Distribution of Agricultural Commodities Selected for the Analysis

(a) Quantity Distribution



(b) Revenue Distribution



(imports) and 3.3b (exports). We chose crops that are of particular economic importance to Jordan and include the following seven crops in our analysis: apricots, barley, cucumbers and gherkins, maize, peaches and nectarines, tomatoes, wheat. Note that since peaches and nectarines are two different crops but are not differentiated in data, we assume all data under this label refers to the first crop listed. That is, we assume only peaches were planted and ignored nectarines. We do the same with cucumbers and gherkins by assuming only cucumbers were planted. In total, the crops selected represented approximately 50% of imports and 53% of exports of agricultural commodities. The distributions of production, imports, and exports quantities (in tonnes) and gross revenue (in USD) for the selected crops ares visualized in Figure 3.4a and Figure 3.4b. We observe Jordan specializes in the production of fruits and vegetables like apricots, cucumbers, tomatoes, and peaches while heavily importing cereal crops like wheat, barely, and maize. The cereal crops play a critical role in food security concerns.

3.1.3 Crop Data

For every crop, we must know the following information: the growth period, crop coefficient values, and starting plant date. Most of this information was directly collected from the FAO handbook, but some information like plant date was determined through other sources (Rawabdeh H. et al. 2010). A summary of this information can be found in Table 3.1.

Table 3.1: Crop Data Summary

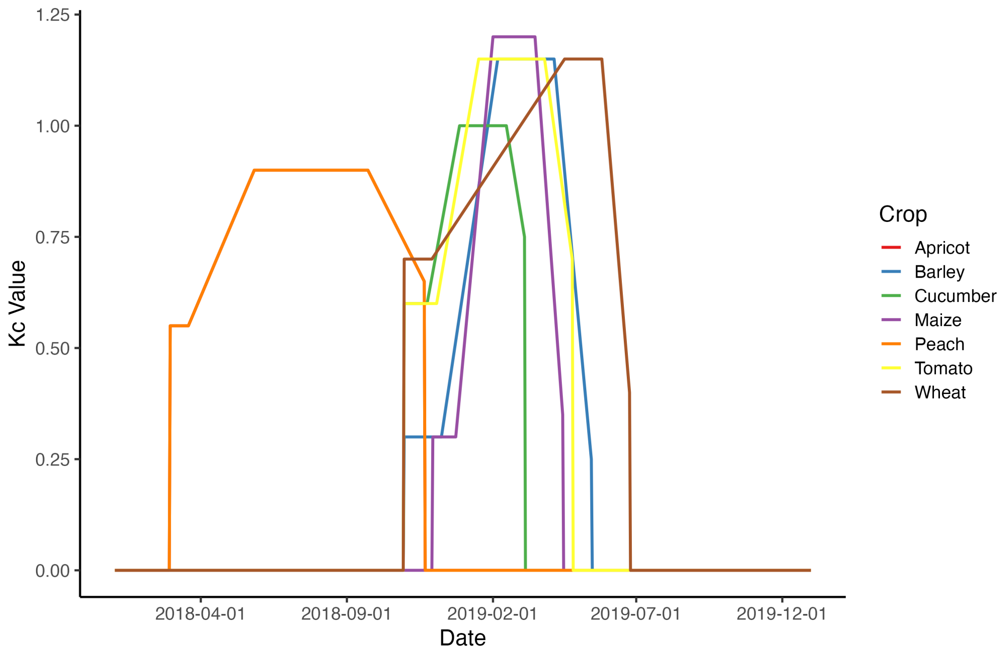
Crop	**Plant Date** yyyy-mm-dd	**Harvest Date** yyyy-mm-dd	**Growth Period** $(L_{init},\ L_{dev},\ L_{med},\ L_{late})$	**Crop Coefficients** $(K_{c\ init}, K_{c\ mid}, K_{c\ end})$
Apricot	2019-03-01	2019-11-26	(20, 70, 120, 60)	(0.55, 0.90, 0.65)
Barley	2018-11-01	2019-05-20	(40, 60, 60, 40)	(0.30, 1.15, 0.25)
Cucumber	2018-11-01	2019-03-11	(25, 35, 50, 20)	(0.60, 1.00, 0.75)
Maize	2018-12-01	2019-04-20	(25, 40, 45, 30)	(0.30, 1.20, 0.35)
Peach	2019-03-01	2019-11-26	(20, 70, 120, 60)	(0.55, 0.90, 0.65)
Tomato	2018-11-01	2019-04-30	(35, 45, 70, 30)	(0.60, 1.15, 0.70)
Wheat	2018-11-01	2019-06-29	(30, 140, 40, 30)	(0.70, 1.15, 0.40)

As noted in the Method Section, the expanded K_c curve was calculated for each commodity as seen in Figure 3.5a. Multiplying this curve with the average ET_o curve shown in the section above yields the average ET_c curve, as seen in Figure 3.5b. Note that since apricots and peaches have the same cropping patterns as shown in Table 3.1, the curves in Figures 3.5a and 3.5b for these crops overlap exactly.

The calculated crop-level coefficients are given in Table 3.2, where CWR, ET_{blue} and ET_{green} are in units of mm while CWU_{blue}, CWU_{green}, WF_{blue}, and WF_{green} are in units of $\frac{\text{m}^3}{\text{tonne}}$. In Table 3.3 we summarize the baseline values of the aggregated water usage and export/import revenues for each crop. For a brevity of notation, we report water usage in terms of million cubic meters, or MCM, and revenue in terms of million USD, or M USD.

Figure 3.5: Expanded K_c and ET_c Curves Across Time

(a) Expanded K_c Curves



(b) ET_c Curves

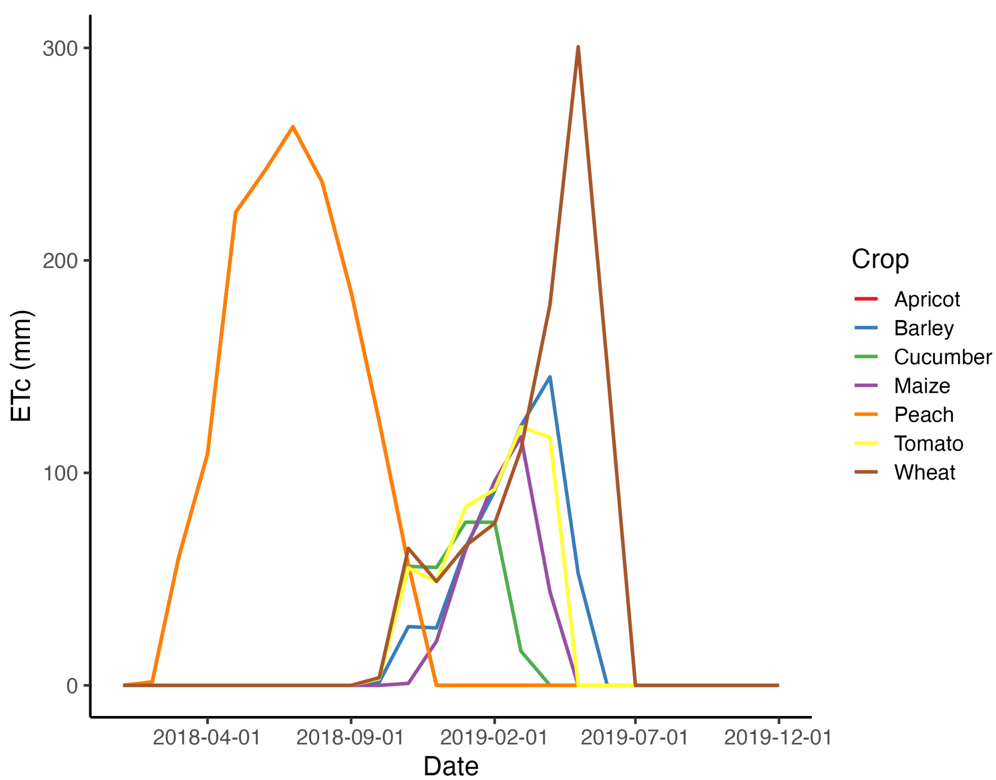


Table 3.2: Crop Statistics

Crop	CWR	ET_{blue}	ET_{green}	CWU_{blue}	CWU_{green}	WF_{blue}	WF_{green}
Apricot	1501	1347	154	13469	1542	802	91.8
Barley	533	225	308	2245	3084	1949	2677
Cucumber	284	0	284	0	2842	0	27.6
Maize	342	34.1	308	341	3084	341	3084
Peach	1501	1347	154	13469	1542	632	72.3
Tomato	522	213	308	2133	3084	35.7	51.7
Wheat	1000	692	308	6917	3084	2891	1289

Table 3.3: Detailed Table of Baseline Production and Aggregate Trade

(a) Baseline Production

Crop	**Production**		
	Quantity (1000 tonnes)	Water Usage (MCM)	Revenue (M USD)
Apricot	26.459	23.641	22.543
Barley	66.618	307.855	32.796
Cucumber	163.484	4.508	52.985
Maize	0	0	0
Peach	79.355	55.883	53.668
Tomato	496.216	43.349	85.597
Wheat	26.361	110.115	14.847

(b) Baseline Aggregate Import

Crop	**Aggregate Import**		
	Quantity (1000 tonnes)	Water Usage (MCM)	Revenue (M USD)
Apricot	0.001	0.001	0.002
Barley	860.236	3975.326	213.411
Cucumber	0	0	0
Maize	770.437	2637.133	161.573
Peach	0.601	0.423	1.087
Tomato	0.018	0.002	0.090
Wheat	851.197	3555.604	203.027

(c) Baseline Aggregate Export

Crop	**Aggregate Export**		
	Quantity (1000 tonnes)	Water Usage (MCM)	Revenue (M USD)
Apricot	11.117	9.933	14.042
Barley	0	0	0
Cucumber	34.944	0.963	21.457
Maize	6.752	23.111	1.520
Peach	70.183	49.425	55.414
Tomato	239.755	20.945	120.288
Wheat	0.413	1.724	0.117

3.2 Optimization Results

Our optimization problem utilized 7 crops for Jordan in 2019. There were a total of $m = 35$ distinct nations involved in trade. The approximate baseline water usage and revenue associated with the 7 crops were -9517.037 MCM and -103.916 M USD, respectively. The negative value for water usage means more water was imported into the nation than exported and domestically used. In the context of this problem and the specified crops, Jordan had a water surplus. On the other hand, the negative value for revenue means the value of the imported commodities was greater than the sum of exported and domestically sold commodities. More simply, Jordan lost money. In terms of optimization, we would want a more negative value for water usage to obtain larger water savings and a more positive value for revenue to reduce the amount of money lost.

As stated in the Method section, we consider two different thresholds for the food security constraint. The first one, which is known as Scenario A, assures that all solutions have an aggregate domestic production quantity that is greater than or equal to a *quarter* of aggregate domestic demand, or 25% food security. The second threshold, or Scenario B, assures that all solutions have an aggregate domestic production quantity that is greater than or equal to *half* of aggregate domestic demand, or 50% food security. We note that, in Scenario B, the food security constraint is not met for the baseline year. In order to achieve 50% food security, Jordan needed to have produced an *extra* aggregate $630,416$ tonnes of the specified crops. As a result, the algorithm was not able to converge to the Pareto Front. Interestingly, however, both Scenario A and Scenario B yield similar solutions, as evident in their objective function spaces.

The *mco* package in R was used to perform the optimization (Mersmann 2020). We ran the NSGA-II algorithm for our vector objective function containing 2 objectives and 4 constraints for 200,000 generations with a population size of 100. In total, there were 728 design elements or variables, but only 229 were being optimized as the remainder were constant values of 0. The crossover probability and distribution index was kept at the defaults of 0.7 and 5, respectively. The mutation probability and distribution index was kept at the defaults of 0.2 and 10, respectively. All code used for the project can be found on GitHub.

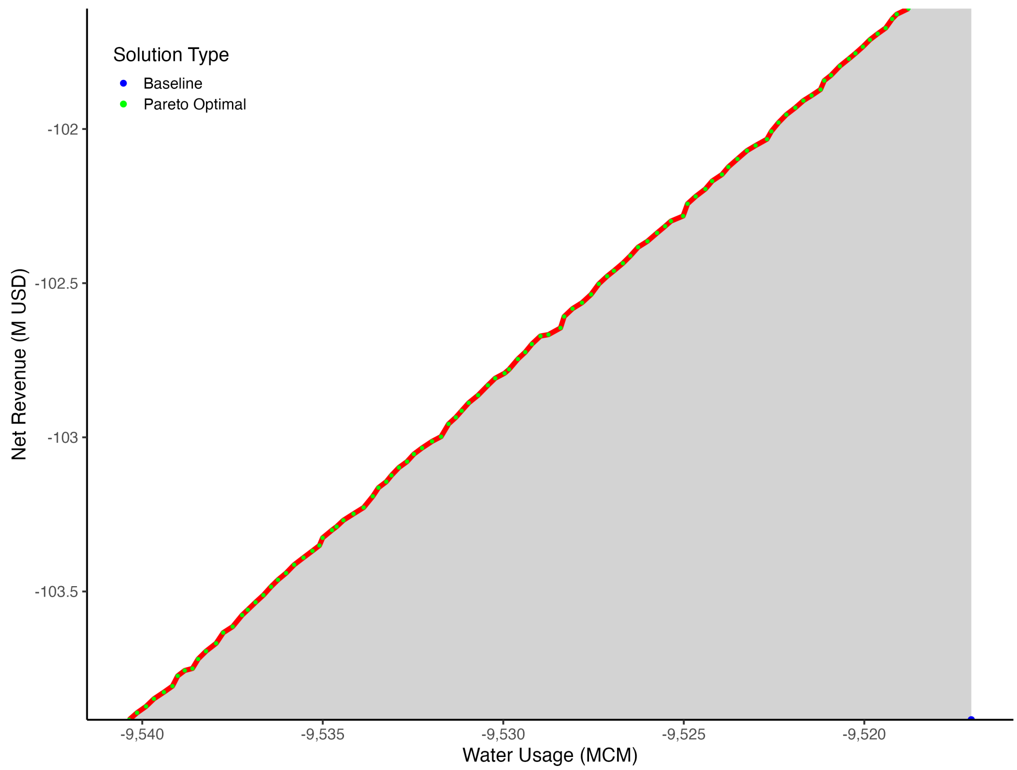
3.2.1 Scenario A: 25% Food Security Constraint

For Scenario A, out of 100 solutions, 100 were Pareto optimal. From the visualization of the objective function space in Figure 3.6a, we see all the Pareto optimal solutions marked with a green circle along the Pareo Front, which is outlined as a red line. The baseline solution ($x = -9517.037$ MCM and $y = -103.916$ M USD) is shown by the blue circle, which is in the bottom right corner. We note that the relative change in the axes are small and hence represent marginal improvements from the baseline year.

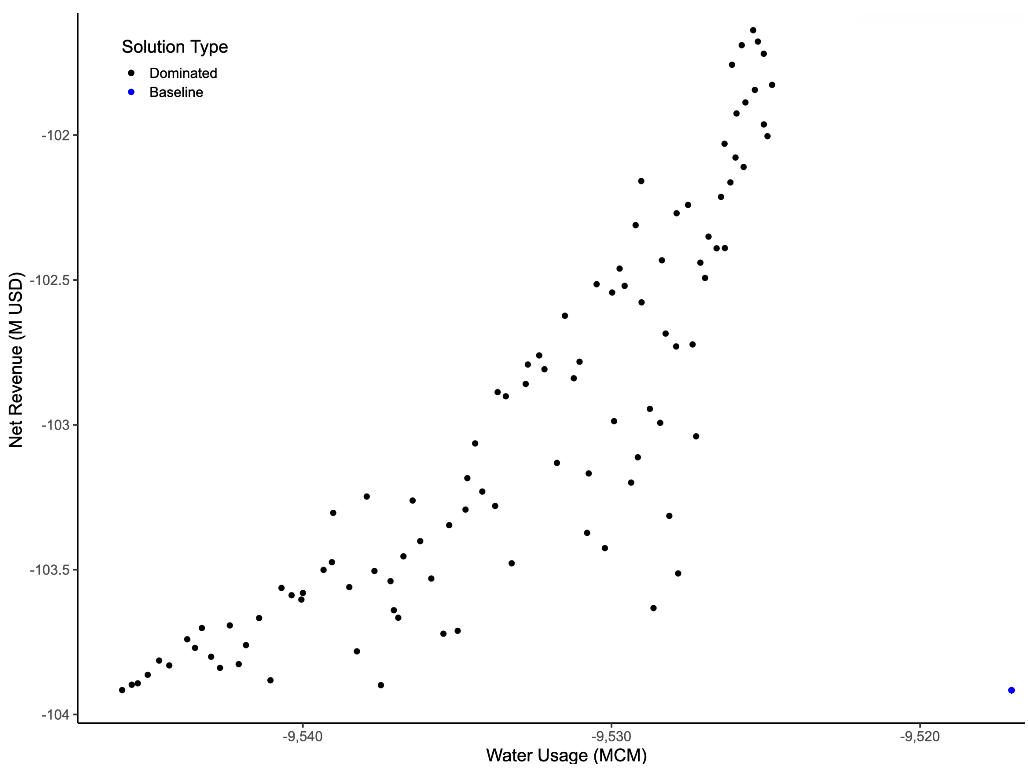
We pick a random Pareto optimal solution—which generated -9518.784 MCM of water usage and -101.604 M USD of revenue—and detail the percent change of aggregated quantities from the baseline in Table 3.4a. The table indicates that if Jordan had essentially stopped importing apricots, peaches, and tomatoes and stopped exporting maize and wheat, then they could have saved an additional 1.737 MCM of water and 2.312 M USD of revenue. This is not entirely surprising because, in terms of water, apricots, peaches, and tomatoes have lower water footprints compared to maize and wheat. High water footprint commodities should not be exported if the goal is to save water usage, and vice-versa. Additionally, apricots, peaches, and tomatoes are cash crops for Jordan. It does not make sense for the nation to import such commodities when they are abundantly produced domestically.

Figure 3.6: Objective Function Spaces of Scenarios

(a) Scenario A: 25% Food Security Constraint



(b) Scenario B: 50% Food Security Constraint



3.2.2 Scenario B: 50% Food Security Constraint

For Scenario B, out of 100 solutions, 0 were Pareto optimal. From the visualization of the objective function space in Figure 3.6b, we observe that while none of the solutions are Pareto optimal, they all dominate the baseline solution, which is located in the bottom right corner. Additionally, the objective function space of Scenario A is very similar to Scenario B, except the solutions are not marked Pareto optimal by the algorithm.

Similar to Scenario A, we pick a random solution—which generated -9527.286 MCM of water usage and -103.286 M USD of revenue—and detail the percent change of aggregated quantities from the baseline in Table 3.4b. The table indicates that if Jordan had essentially stopped importing apricots, peaches, and tomatoes and stopped exporting maize and wheat, then they could have saved an additional 10.249 MCM of water and 0.63 M USD of revenue.

Table 3.4: Percent Change of Random Solution from Baseline of Scenarios

(a) Scenario A: 25% Food Security Constraint

Crop	**Production**	**Aggregate Import**	**Aggregate Export**
Apricot	0%	-100%	-0.004%
Barley	-0.003%	0%	0%
Cucumber	0%	0%	-0.007%
Maize	0%	-0.749%	-93.409%
Peach	0%	-100%	-0.004%
Tomato	0%	-100%	-0.001%
Wheat	0%	-0.039%	-100%

(b) Scenario B: 50% Food Security Constraint

Crop	**Production**	**Aggregate Import**	**Aggregate Export**
Apricot	0%	-100%	-0.480%
Barley	0%	-0.004%	0%
Cucumber	0%	0%	-0.880%
Maize	0%	-0.223%	-91.528%
Peach	0%	-99.001%	-0.041%
Tomato	0%	-94.350%	-0.033%
Wheat	0%	-0.173%	-95.639%

Chapter 4

Discussion and Conclusion

4.1 Discussions of Results

Using data from Jordan in 2019, we have found better solutions, in terms of production and trade quantities of a selection of agricultural commodities, that would decrease the country's water usage while simultaneously increase its revenue. The multiobjective optimization algorithm was run under two different scenarios that differ in the food security constraints. We note that although Scenario A found Pareto optimal solutions and Scenario B did not, the objective function spaces of both are similar. We next provide some intuition behind why the algorithm failed to find Pareto optimal solutions in Scenario B.

For Scenario B, we defined the food security constraint as being 50%, or that at least half of all aggregate domestic demand must be met through internal production. This constraint was not met in the baseline year by $630,416$ tonnes. Also note that due to how we defined the upper bounds for each design variable, it would have been impossible to meet this constraint for any solution in the feasible domain of Scenario B. To elaborate, consider if domestic demand were $DD = 20$ and the baseline domestic production quantities was the vector $\overrightarrow{PQ} = \begin{bmatrix} 5 & 6 & 7 \end{bmatrix}$. Note that $\overrightarrow{PQ} \cdot \overrightarrow{1} \geq \frac{DD}{2}$ is false. Because of how we configured our model and bounds, it is impossible determine alternative values of domestic production whose aggregate value will be greater than or equal to domestic demand if the baseline aggregate value of domestic production does not meet this condition in the first place.

Additionally, the way we constrained the bounds of the design variables also explains why the solutions from Scenario A and B have marginal improvements in both objectives. One of the core assumptions of our model is that we assume the baseline configuration represents the "maximum capacity" of the target nation. We assume if the nation domestically produced b amount of one commodity, then they only had the capacity to produce a value between $[0, b]$. Meaning, if the nation could produce 10 tonnes of wheat, then they could have certainly produce 9 tonnes or less. Had we allowed the upper bound to be greater than its corresponding baseline value for each design variable, then we would have to determine how large the upper bound should be, or just how much the nation could produce, import, and export more for each commodity. Modeling this in a realistic scenario is challenging because the algorithm could return a solution for production values that is physically impossible for the target nation to produce. The same could be said for trade. Obviously, allowing the upper bounds to be larger would produce solutions substantially better in terms of both objectives, but we chose not to due to the reasoning provided above.

The maximum capacity bounds also explain the small change in percentages from the baseline year for a specific optimal solution, as shown in Tables 3.4a and 3.4b. Domestic production showed essentially 0% relative change. This is because the food security constraint is the only constraint dependent on domestic production quantities and therefore changes in domestic production can be very "costly" in terms of getting solutions from the algorithm.

It is important to note that from Table 3.3b, we see Jordan imported less than 1000 tonnes in total of apricots, peaches, and tomatoes in the baseline year.While the small quantities are consistent with results from the optimization, it would be interesting to investigate why Jordan decided to import such fractional quantities of these commodities in the first place, especially when they could easily produce them domestically. The same could be said for the fractional quantity of exports in wheat, as interpreted from Table 3.3c.

4.2 Limitations

Any model that measures water usage of commodities requires a variety of climate variables. In our analysis, we faced data limitations regarding the climate data. The weather data we could freely access with IEM had just 3 weather stations from Jordan when there are 20 stations available through the JMD. Purchasing data from JMD is only available at monthly intervals and is expensive. It can be argued that our CWR calculations were not completely representative as we only used the average of 3 stations. Additionally, it can be argued that since a majority of the farming happens in the Jordan Valley, data from weather stations near that region will be the most representative in CWR, or crop water requirements, calculations.

In terms of economic data, all information regarding prices and quantities is yearly data. Since the output solutions of the model are also aggregate quantity values, there are some real-world details the model does not capture. For example, from the FAOSTAT TM database we know Jordan imported $170,000$ tonnes of barley for a total value of $43,536,000$ USD from Argentina in 2019, but we do not know whether this trade was part of a series of trades at various rates or a single trade at a fixed rate. Our model assumes that, if Jordan is to import barley from

Argentinian in 2019, it must import x tonnes where $x \leq 170000$ and at a rate of 267.85 USD per tonne. In reality, Jordan and Argentina may have an agreement where the rate of 267.85 USD per tonne is honored only if there is a minimum import of $170,000$ tonnes. It may also be the case that Jordan and Argentina conduct several independent trades and it just so happens the average rate of each import transaction of barley was 267.85 USD per tonne. Our model does not capture such sophistication of real-world economics.

Additionally, our model optimized trade quantity values down to the nation level. Such level of detail might not be necessary if a majority of the trade quantity values come from a handful of nations. For example, out of the 35 countries involved in trade with Jordan in 2019, Jordan exported apricots to just 7 countries and wheat to just 2 countries. In such situations, it might be more appropriate to optimize trade at an aggregate level, which would significantly reduce the model dimension and computational cost.

The results regarding food security are interesting. In the baseline case, Jordan was roughly meeting 28.87% of it's aggregate domestic demand through domestic production. Achieving a higher food security percentage constraint will require increasing the upper bounds of the design variables for domestic production quantities. As we explained earlier, the results of the 25% and 50% food security constraints are not vastly different and both yield solutions that outperform both objectives relative to the baseline. Even if we could determine the optimal food security percentage, our constraint ignores the nutritional value of the crops. For example, if Jordan produced an extra $630,416$ tonnes of cucumbers and tomatoes for the baseline year, then they would have met 50% food security. While cucumber and tomatoes are prominent in Jordanian cuisine, most people will still incorporate cereal crops like maize or wheat in their diet as their main source of energy. Defining a food security constraint that incorporates such aspects is important in understanding the significance of optimizing Agricola commodity quantities.

Our results showed that by just reducing the production, imports, and exports of particular commodities, Jordan could further optimize their water usage and revenue by reducing imports of apricots, peaches, and tomatoes while also reducing exports of maize and exports. Though we use 2019 as the baseline year, most of crop, climate, and economic data are representative of a typical year. The results of the food security provide an interesting perspective on how water-scarce nations like Jordan struggle to achieve food security in terms of percentage of domestic production meeting domestic demand. In the future, utilizing a model with a refined food security constraint and larger upper bounds can provide more information on how Jordan could further specialize its agricultural economy.

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