J Environ Stud Sci (2016) 6:62–76
DOI 10.1007/s13412-016-0372-y

Spatial computing perspective on food energy and water nexus

Emre Eftelioglu[1] · **Zhe Jiang**[1] · **Reem Ali**[1] · **Shashi Shekhar**[1]

Published online: 11 February 2016

Abstract In the coming decades, the increasing world population is expected to grow the demand for food, energy, and water resources. In addition, these resources will be under stress due to the climate change and urbanization. Previously, more problems were caused by piecemeal approaches analyzing and planning those resources independent of each other. The goal of the food, energy, and water (FEW) nexus approach is to prevent such problems by understanding, appreciating, and visualizing the interconnections and interdependencies of FEW resources at local, regional, and global levels. The nexus approach seeks to use the FEW resources as an interrelated system of systems, but data and modeling constraints make it a challenging task. In addition, the lack of complete knowledge and observability of FEW interactions exacerbates the problem. Related work focused on physical science solutions (e.g., desalination, bio-pesticides). No doubt these are necessary and worthwhile for FEW resource security. Overlooked in these work is that spatial computing may help domain scientists achieve their goals for the FEW nexus. In this paper, we describe our vision of the spatial computing's role in understanding the FEW nexus using a Nexus Dashboard analogy. From a spatial data lifecycle perspective, we provide more details on the spatial computing components behind the Nexus Dashboard vision. In each component, we list new technical challenges that are likely to drive future spatial computing research.

Keywords Food, energy, and water nexus · Spatial computing · System of systems · Sustainability · Precision agriculture

✉ Emre Eftelioglu
emre@cs.umn.edu

Zhe Jiang
zhe@cs.umn.edu

Reem Ali
alireem@cs.umn.edu

Shashi Shekhar
shashi@cs.umn.edu

[1] University of Minnesota, Minneapolis, MN, USA

Introduction

Over the last couple of decades, food, energy, and water (FEW) resources were used exorbitantly in production and consumption, which triggered signals of future resource scarcity. Many future scenarios indicate that these vital resources will be under increasing stress across the globe due to population growth, urbanization, and climate change, which was caused by the failure of limiting the greenhouse emissions by policymakers. Traditionally, food, energy, and water resources were studied independently from a single system perspective. Figure 1 shows each food, water, and energy resource as an individual system. For example, in the water system, water comes from rivers and lakes, and is consumed by human activities and surface discharge. In the energy system, energy comes from fossil fuels, solar radiation, nuclear power, and hydroelectric plants, and is consumed by residential and industrial activities.

However, these systems are highly interconnected and interdependent on each other. Figure 2 shows a representative schema that illustrates the interconnections and interdependencies between food, energy, and water systems. For example, the interdependencies can be seen in energy production where water is used for cooling nuclear power plants, for energy generation in hydroelectric power plants, and for the extraction of coalbed natural gas for thermoelectric power

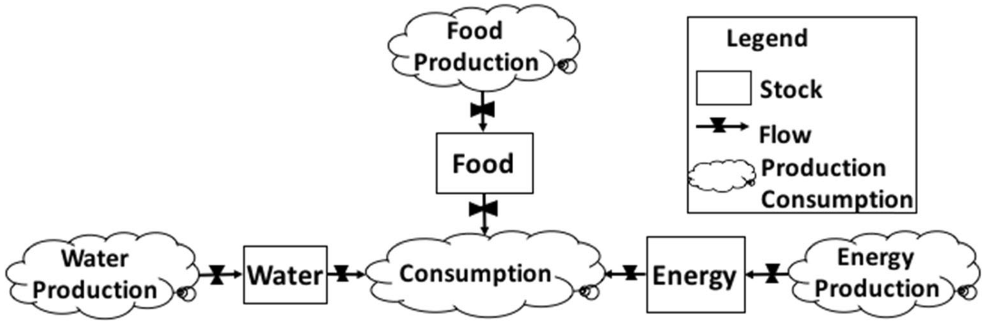


Fig. 1 Individual food, energy, and water systems

plants (Hoff 2011; NSF 2014a; Healy et al. 2015). Similarly, food (i.e., agricultural products) is used as biofuel for energy generation. Water is used both to irrigate agricultural fields and energy generation (e.g., hydroelectricity, power plant cooling).

Previous efforts were mainly focused on improving one resource while ignoring others. However, due to the interconnections and interdependencies between FEW resources, solutions from a single system perspective may have unintended consequences in other systems (Scott et al. 2011; Mohtar and Daher 2012; Scott et al. 2015). Often, these unintended consequences have negative impacts that require more efforts to fix. For example, the increased use of fertilizers to enhance crop yield requires more energy use (for fertilizer production) and causes greenhouse gas emissions. Moreover, the run-offs from the fertilizers on agricultural land cause surface and underground water pollution (Hellegers et al. 2008; Andrews-Speed et al. 2012; Pierre Guillibert 2015; UNU-FLORES 2015). Such problems are generally poorly understood, unanticipated, and overlooked unless they cause a huge impact on another resource. For example, in 2002, excessive use of fertilizers for crop production in the US Midwest brought nutrients into the Gulf of Mexico through rivers, and triggered a large-scale growth of algae and the subsequent loss of dissolved oxygen in the water. Fish died and the area became a dead zone (Rabalais et al. 2002). Aside from the obvious Food-Water interaction in this problem, there is also an Energy component. First, around half of the US corn production currently goes to biofuels, which imposes a stress on Food production. Second, fertilizer production requires energy and unnecessary or extreme fertilizer use causes more energy consumption.

In order to address these issues, food, energy, and water resources should not be considered as independent systems,

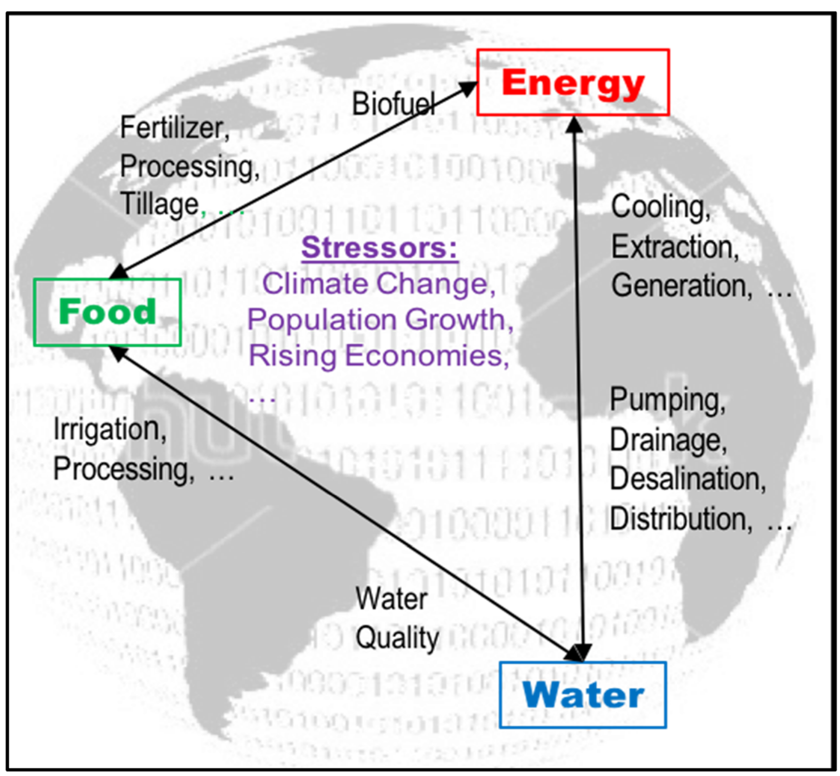


Fig. 2 Interaction of food, energy, and water systems

but a system of systems, which consists of individual systems as well as the interconnections and interdependencies between those as shown in Fig. 3. The goal of the system of systems "FEW nexus" approach is to reduce such unintended consequences by understanding, appreciating, and visualizing the interconnections and interdependencies in the FEW resources at local, regional, and global levels (Hellegers et al. 2008; UNU-FLORES 2015). Thus, it is a decision-making framework, which employs a system of systems perspective, to identify externalities (i.e., the effects of resources to each other), monitor present conditions, simulate future impacts and show early warnings, explore feasible solutions, and help policymakers achieve a greater policy coherence. The FEW nexus approach aims to achieve resource sustainability and availability by applying the nexus framework on a local level of decision-making and also a regional and global level of policymaking processes.

National and international agencies have recently begun to consider the research challenges in understanding the FEW resources from a nexus perspective (Bazilian et al. 2011;FEWSNET 2013; Lundy and Bowdish 2014; NSF 2014b; NSF 2015; Pierre Guillibert 2015; U.S. Dept.of State 2015). A report by the Food and Agriculture Organization of the United Nations called for stakeholder dialog based on empirical evidence, scenario development, and response options (Flammini et al. 2014). A 2014 report by the National Science Foundation Mathematics and Physical Sciences Advisory Committee identified key areas where physical science could address the FEW challenge such as developing desalination technologies to increase sustainable water supplies for agriculture, and improving crop protection via biopesticides and genetic techniques. The US Department of Energy also published a report summarizing the challenges and opportunities for understanding the water-energy nexus (Healy et al. 2015). The report highlights promising technologies such as advanced materials for energy production, wastewater recovery for reducing the environmental impacts of energy production, and cooling technologies for energy producing facilities (i.e., nuclear plants), etc.

These are necessary and worthwhile recommendations for achieving FEW resource security. Overlooked—or perhaps taken for granted—in these reports is the role that spatial computing and technologies will play in the FEW nexus research efforts as well as on different levels of policymaking. Every interaction in a food, energy, or water system takes place within a geographic context. FEW nexus researchers will need high-quality geographic (i.e., spatial) data and efficient computational tools to manage, analyze, and make sense of this data.

Precision agriculture is an illustrative example of how spatial computing can help domain scientists from a FEW nexus perspective. It is an agricultural decision support system and its tools, which allows site-specific (i.e., location aware) use of water, pesticide, and fertilizers by measuring crop health, soil nutrients, and moisture. It enables farmers improve yields, reduce unnecessary applications of fertilizers and pesticides, preserve natural resources, and contend with impending weather events (NRC 1997; NAP 1997; Plant et al. 2000; McBratney et al. 2005). Apart from the benefit of improving yields, precision agriculture improves the efficient use of energy and water as well. In agricultural practices, one of the implicit costs is the cost of energy. From the application of fertilizer and seeds to pumping irrigational water, energy is widely used for agriculture. Moreover, the indirect costs of the energy use in fertilizer production and desalination of irrigational water are also increasing the energy cost. By precision agriculture, the water run-offs are prevented and water is used only on the required locations in the field depending on the soil moisture levels measured by soil sensors. Therefore, by using precision agriculture for food production, not only the food aspect of FEW nexus is improved, but also energy and water is used more efficiently.

Precision agriculture uses a wide variety of spatial computing tools in order to achieve its success. The spatial data that is

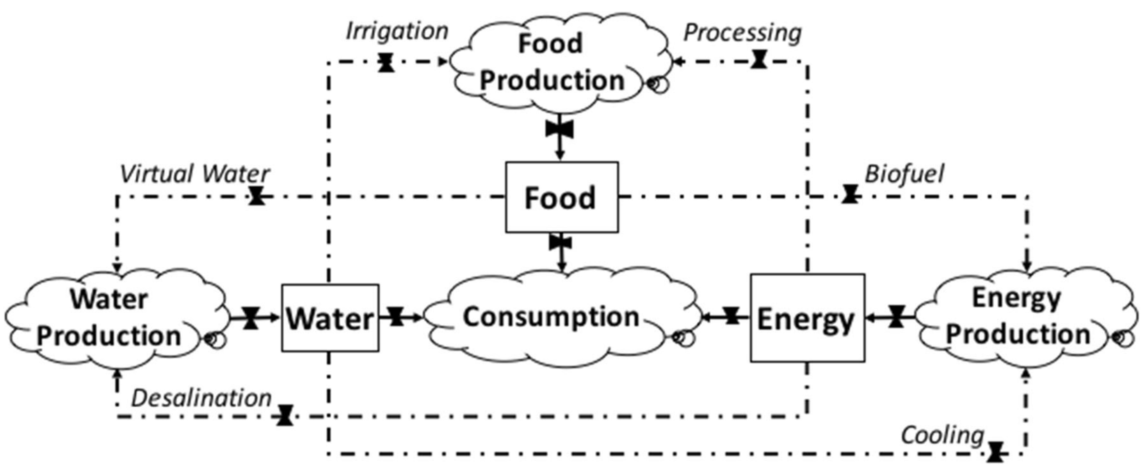


Fig. 3 FEW system of systems

used for precision agriculture is collected from a variety of sources including unmanned aerial vehicles (UAV) and satellites that collect remote sensing imagery, soil sensors installed in the ground, and tractors that collect soil samples from a variety of locations in the field. The key technology that allows merging these data is the location information, which is made available by Global Navigation Satellite Systems (GNSS) (GNSS 2011; NAS 2012). Once these datasets are collected, they are stored in spatial databases, which allow location-based queries about soil properties, plant properties, farm management practices, and yield. For example, queries such as "where is the location in the field with high moisture and low fertilizer?" can be easily answered using the spatial databases. Stored spatial data is later used for spatial data mining tasks such as detection of hotspots of the locations with fewer nutrients in the field. Similarly, path planning and navigation systems help efficiently traversing farms without unnecessary soil compaction, spatial statistical analysis tools help delineate management zones in large farms, and spatial decision support systems help optimize yield while preserving the energy and water use by site-specific irrigation selection. Also, computerized map visualizations allow farmers to understand inter- and intra-field variability. These spatial computing techniques are also applicable to many FEW problems including but not limited to efficient and sustainable use of resources by precision agriculture practices, better resource management by virtual water trading (Allan 2003; Hoekstra and Hoekstra 2003), better land usage by geodesign and supply chain relocation (Min and Zhou 2002; Melo et al. 2009), etc.

In this paper, we describe our vision of the role of spatial computing in understanding the FEW nexus using a Nexus Dashboard analogy. From a spatial data lifecycle perspective, we provide more details on the spatial computing components behind the Nexus Dashboard vision. For each component, we list new technical challenges that are likely to drive future spatial computing research. It is worth noting that since truly deep integration at the nexus of all three sectors is still an emerging field, demonstrating how to do it with detailed examples is very challenging. Therefore, in order to illustrate spatial computing approaches and visions, and to focus on the lessons that can be drawn from the examples that do exist, we sometimes use examples that connect just two sectors (i.e., food-water, energy-water, food-energy). Finally, it is worth noting that this paper should be considered as a review paper instead of a novel research paper with new results.

Next, "Background" section gives brief background information on the FEW Nexus and Spatial Computing. "Spatial computing vision and challenges" section shows our vision of the Nexus Dashboard, where each component of the Nexus Dashboard is described in a subsection. Finally, "Summary" section summarizes the paper.

Background

In this section, we will first introduce background information on the FEW Nexus and Spatial Computing.

Food energy and water nexus

In the coming decades, the world population is projected to grow significantly resulting in increased strains on the world's limited food, energy, water, and other natural resources. Furthermore, these strains may be amplified due to the effects of global climate change and increasing urbanization. To complicate matters as illustrated in Fig. 2, the food, energy, and water systems are coupled through complex interactions. For example, increasing reliance on biofuels puts strain on limited land and water resources, hence on food production. Thus, attempts to achieve energy security by increasing the production of biofuels without regard to how it may impact water or food security may lead to unanticipated surprises for food and water security. Indeed, the rise in food prices in many parts of the world in 2008 was attributed to increases in subsidies for biofuels (Wright 2009). Similarly, incentives to farmers for increasing food production have depleted water resources (e.g., Aral Sea, Ogallala aquifer) and affected water quality (e.g., dead zones in many coastal areas). In recent years, drought and heat affected the US nuclear power production and barge-based coal transportation (Scott et al. 2011). Hence, there is a growing recognition of the need for a new approach to understanding the complex interactions between the food, energy, and water subsystems of the food-energy-water nexus as a function of population dynamics, climate change, and other factors.

The food-energy-water nexus is among the highest priorities of the United Nations. It is increasingly figuring among the top priorities of many nations including the USA. For example, a recent National Intelligence Council report identified the food-energy-water nexus among the greatest challenges facing our world in the coming decades, and a USDOE report listed challenges and opportunities in the Water-Energy nexus. The NSF has requested \$70 M for FY16 to start a multi-year cross-directorate initiative focused on "Innovations at the Nexus of Food, Energy and Water Systems (INFEWS)." This year, the NSF has sponsored a series of workshops aimed at engaging diverse research communities to identify multi-disciplinary INFEWS research challenges (and opportunities).

A recent review article (Liu et al. 2015) discusses the necessity of system integration, a nexus approach integrating individual components such as food, energy, water, air, land, people, etc. Such nexus view can help anticipate otherwise unpredicted consequences, estimate trade-offs, bring co-benefits, and seek common grounds for different and often competing interests. The article reviews recent advances on several system integration frameworks, including those for ecosystem services, environmental footprint, and planetary boundaries. For instance, spatial integration is important for landscape planning in ecosystem services with the possibility of coordination across space. An example is that reforestation in upland areas above an agriculture field can help reduce soil erosion, protect waterway, minimize flood, and facilitate sustainable agricultural production. Applications of system integration frameworks include biofuel and virtual water. Although system integration or the nexus frameworks have led to fundamental discoveries and possible applications, the article also points out that further efforts are in need. One important research need is to develop and use new powerful tools. Examples include spatially explicit life cycle assessment, supply chain management, and multilevel modeling. Moreover, as more high-resolution data become available, which are spatial and spatiotemporal in nature, big data tools are necessary to effective and efficient data integration, management, and analysis.

Spatial computing

Spatial computing embodies the ideas, tools, and technologies that integrate and leverage the spatial and temporal information associated with data. Although previously used by a small group of highly trained professionals (e.g., experts in oil exploration companies, etc.), today almost everyone uses mobile technologies that are built using spatial computing (e.g., GPS). Spatial computing is also used by organizations for tasks such as site selection, asset tracking, facility management, navigation, and logistics (Shekhar et al. 2015b).

In order to achieve its tasks, spatial computing uses specific tools on different levels of the data lifecycle (i.e., data collection, data management, data mining and data visualization, and decision support) (Shekhar et al. 1999; Shekhar et al. 2015a, b). These are as the following:

- First, *spatial data collection* is done by measurements from different locations on Earth as well as subsurface, surface, and atmospheric sensor and human readings. Often, the collected data has a component that describes its location on Earth as well as a temporal component that keeps information about when this data is collected in time.
- The collected spatial data are often points (e.g., sensor locations and readings), lines (e.g., road segments, streets), polygons (e.g., countries, lakes), etc. Moreover, this data is often used for queries such as "Which countries have coast to Atlantic Ocean?" However, traditional database management systems use one-dimensional data types (i.e., number) as well as indexes that cause complex programming and long execution times for such queries. Thus, *spatial database management systems* (*SDBMS*) are developed to manage two-dimensional and three-dimensional spatial data and facilitate spatial queries. SDBMS can represent collected data as lines, points, and polygons and can do query operations such as distance and range queries, nearest neighbor, etc.
- Similarly, due to the fact that "Everything is related to everything else, but near things are more related than distant things." as Tobler's first law of geography states (Tobler 1970), traditional data mining tools are inadequate and sometimes misleading for spatial data due to their general assumption of independent and identically distributed observations. Therefore, spatial computing has specialized *spatial data mining* tasks such as co-location and co-occurrence pattern mining, hotspot detection, and spatial change detection of specific spatial phenomena.
- The collected data and the outcomes of data mining tasks are visualized by *spatial visualization tools* that facilitate domain scientists' work by visualizing geo-located data that sometimes is too complicated to illustrate.
- The outcomes of these spatial tools as well as the visualizations are used in *spatial decision support systems* in order to facilitate domain users' tasks. Such spatial decision support tools may control and monitor the water distribution in a city, may suggest the amount of fertilizer use in a specific location in an agricultural field, or may reroute electricity distribution over a city in case of a failure.

Spatial computing vision and challenges

We believe that spatial computing may offer insights into the interactions and interdependencies of the FEW nexus. We envision a Nexus Dashboard, analogous to the dashboard of a car that would serve to provide future projections and early warnings. A car's dashboard shows the current conditions (i.e., engine temp, speed, rpm, etc.) and warnings (i.e., engine failure, tire pressure, etc.) by its indicator lights and gauges. Similarly, as illustrated in Fig. 4, the Nexus Dashboard may help domain scientists watch current trends and interactions between the FEW resources and produce alerts and warnings for future resource chokepoint events. Figure 5 shows several chokepoint events that happened in the last couple of decades. For example, excessive water usage for agricultural purposes caused the Aral Sea to shrink to less than half of its original size in a couple of decades. Similarly, in July 2012, the electricity subsidy for agricultural water pumps in South Asia during a drought led to power grid failure, triggering the largest blackout on earth (Webber 2015). Our Nexus Dashboard analogy may help bring early warning to avoid such wide spreading crises.

The Nexus Dashboard is a spatial decision support tool, which consists of several spatial computing components that

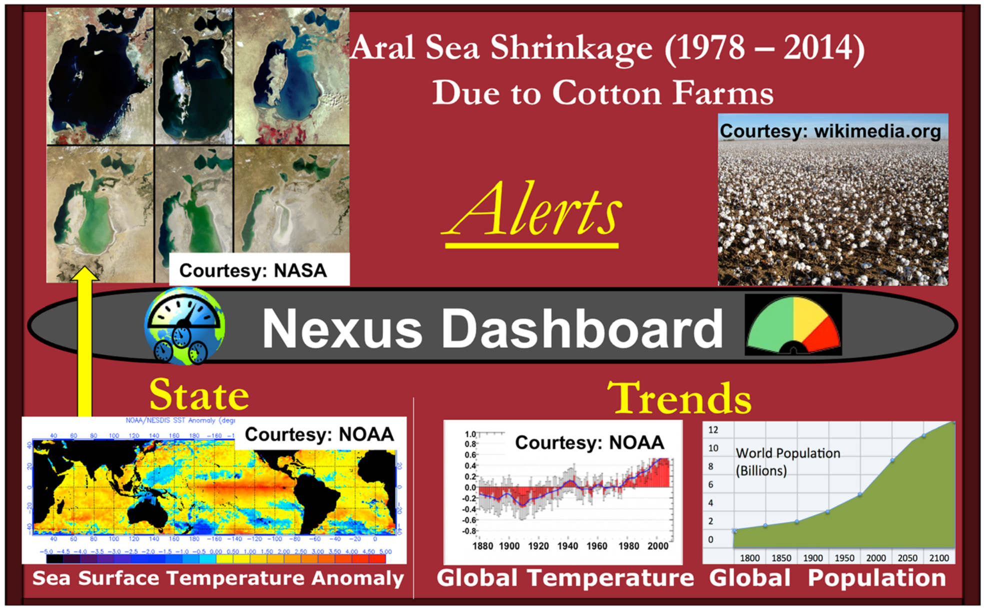


Fig. 4 Nexus Dashboard—an illustration of continuous monitoring, trends and alerts

will be discussed from a spatial data lifecycle perspective. These components include spatial data collection, data management, data mining, and visualization, as illustrated in Fig. 6. In the next subsections, we describe current spatial computing techniques within each component, their relevance to the FEW nexus (e.g., through the precision agriculture example), as well as new spatial computing challenges arising from the FEW nexus.

Spatial data collection (observations)

Scientific data collection has been revolutionized by many spatial computing technologies. Although different spatial data collection technologies exist, there are representative spatial computing technologies that are widely used by domain scientists, which may improve the FEW nexus thinking.

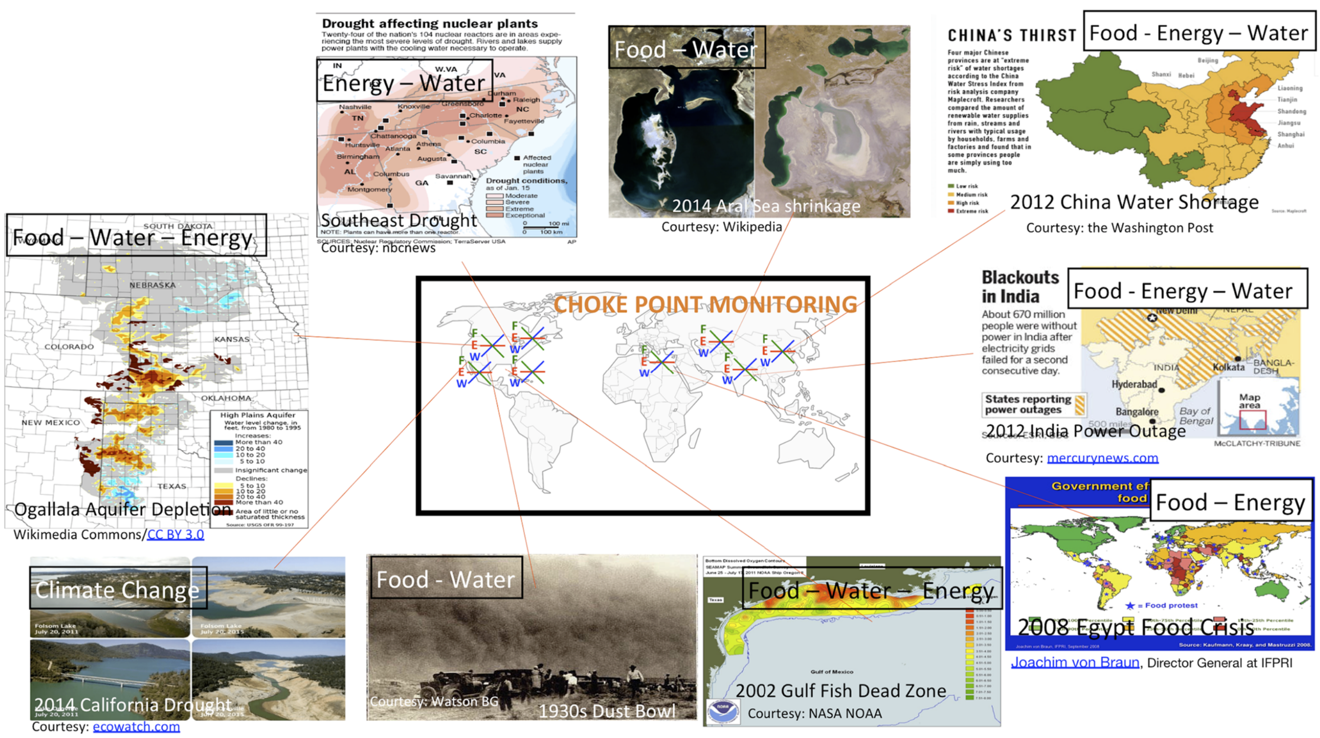


Fig. 5 Food, energy, and water choke point locations that occurred in the last decade

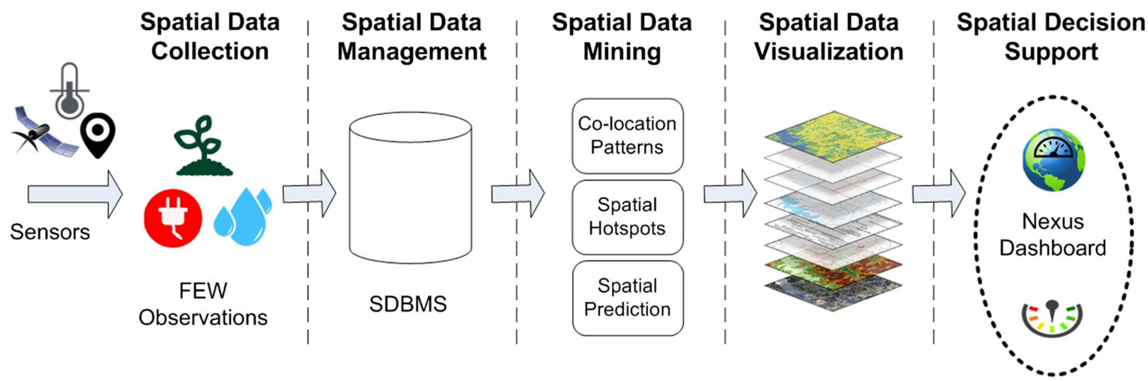


Fig. 6 Nexus Dashboard components

Remote sensing is one of those technologies (Zainuddin et al. 2006; Lillesand et al. 2009; Campbell and Wynne 2011; Zhao et al. 2012; NRC 2014). Previously, land surface monitoring (e.g., land cover changes, urbanization, population growth, water resources) was done by field surveys. These were done by extensive manual labor and were taking a lot of time to process. Due to these limitations, those were limited to relatively smaller areas. Today, sensor-equipped aerial vehicles including satellites and unmanned aerial vehicles (UAV) collect these remote sensing data for larger areas in a shorter time. Remote sensing technologies are widely used in the field by precision agriculture applications in large farms. For example, crop health is monitored by Normalized Difference Vegetation Index (NDVI) imagery, which determines the greenness of a plant. Using these collected remote sensing data, the locations where fertilizer and irrigations are needed are determined. Finally, variable rate applicator devices apply fertilizer and water just as needed.

In addition to the precision agriculture applications, remote sensing technology is widely used in surface water mapping, land cover prediction, and wind map creation. Moreover, specialized instruments for specific remote sensing tasks allow monitoring of precipitation, land imaging for agriculture, airborne snow observation, infrastructure monitoring, and emergency response. Figure 7 shows NASA Earth Science satellites with specialized remote sensing instruments as of September 2015. For example, Landsat 7–8 satellites have sensors on different bands. Those sensors include near infrared (NIR) which helps determine land cover by Normalized Difference Vegetation Index (NDVI) imagery, a deep blue band sensor for coastal/aerosol studies, and a shortwave infrared band for cirrus detection. Also, SWOT and GRACE satellites are used for water resources research, and SUOMI-NPP satellite imagery can be used to track the energy consumption using the earth night lights.

Although they are not sensing remotely, ground sensors are also important for spatial data collection. These include (but are not limited to) ocean sensors that keep track of eddies, groundwater sensors (probes in wells) that are used to measure groundwater levels, and specialized soil sensors for a variety of tasks such as humidity, and soil nutrition. For example, in precision agriculture, tractors that are equipped with soil sampling devices collect samples from different locations in the field and this data is used to determine the nutrition levels of the soil. Such data collected from different sources is required to be matched altogether in order to use in specific applications. For example, the soil sensor data, crop health data, and soil humidity data are all collected by different sensors and technologies and with different sampling and data collection rates. Data from different sources are matched together using their location information. Location information is created thanks to the Global Navigation Satellite Systems (GNSS).

The Global Positioning System (GPS) is an example of a space-based GNSS (GNSS 2011) that provides location and time information anywhere on Earth where there is an unobstructed line of sight to four or more navigation satellites (out of a few dozen) (Parkingson and Spilker 1996). GPS is widely used for precision agriculture tasks, electric power distribution grid synchronizations, water resource monitoring, etc. Using the location information from GPS-equipped tractors, remote sensing imagery with location information, and the variable rate applicator devices, large farms applying precision agriculture methods can determine precisely where the fertilizers and water is needed.

Current spatial computing techniques such as the Global Positioning System (GPS), remote sensing satellites, and aerial planes, as well as ground sensor networks can provide an opportunity to leverage rich geo-contexts to support global-scale data collection of FEW resources. We envision that a finer resolution remote sensing and more precise GNSS technologies may extend the current methods such as precision agriculture from larger farms to smaller scales. Moreover, such technologies may allow decision-makers to make more precise future projections.

However, finer resolution remote sensing will create challenges for spatial computing. Current technologies for data collection will be inadequate for finer resolution data. In addition, improved temporal resolutions will require faster collection and processing capabilities. Thus, current methods should be redesigned to address these issues.

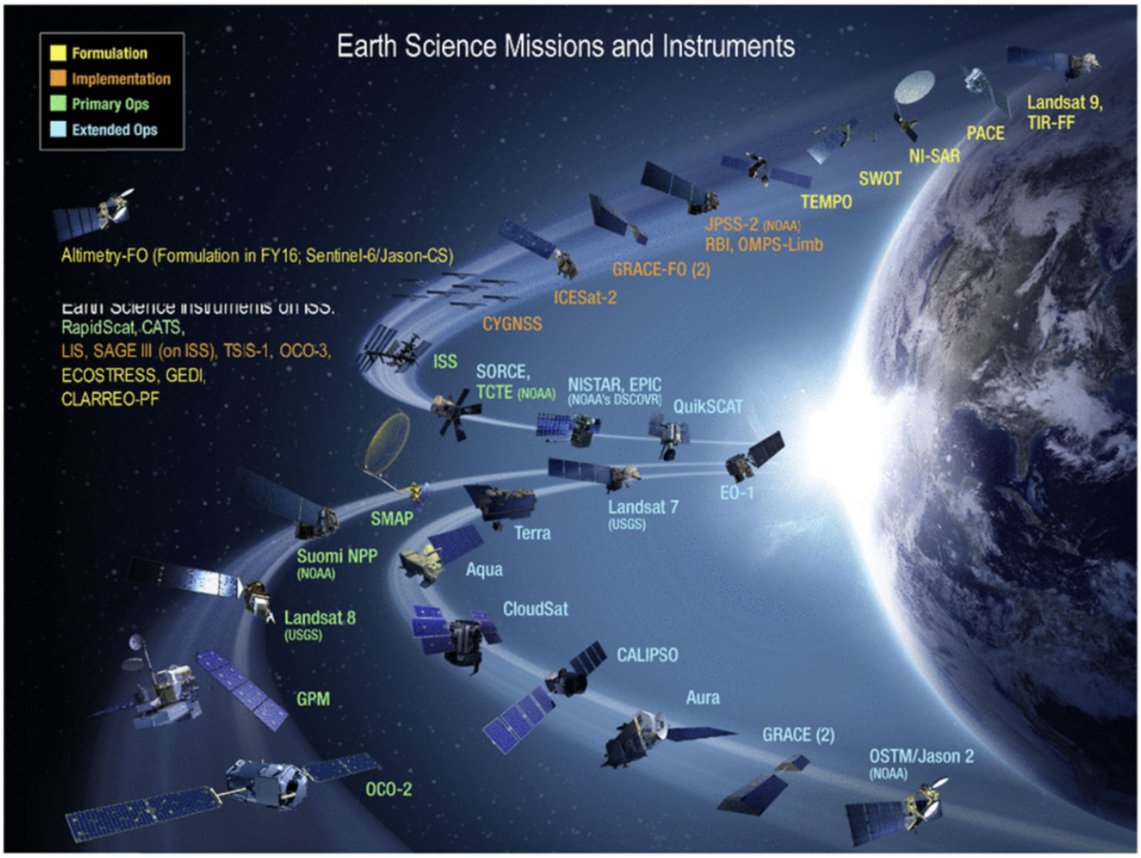
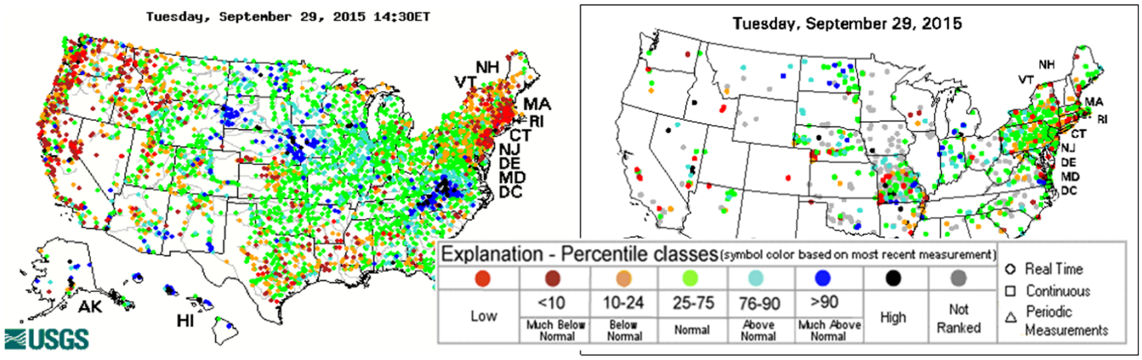


Fig. 7 NASA Earth Science Division mission and instruments as of September 2015 (NIC 2015a; NIC 2015b)

Another challenge is the "observability" even though recent earth observation platforms (e.g., GEOSS, Earth Observatory) show promise for collecting rich observation data. For example, in order to understand the water-energy nexus and determine water availability for current and future energy production, data collection on water quality and quantity is necessary. For water quantity monitoring, the US Geological Survey (USGS 1997) currently maintains a surface water-gauging network that monitors thousands of sites nationwide as well as groundwater observation wells. Figure 8a shows surface water measurement stations, and Fig. 8b shows groundwater measurement stations. The spatial coverage and temporal frequency of observations from groundwater stations are more limited compared to surface water observations stations (Fig. 8). For example, among 850,000 wells, only 20,000 wells have measurement in 2013, and only about 2500 wells have daily or more frequent measurements. For water quality monitoring, the US Geological Survey operates continuous recorders at about 1700 sites across the country, and discrete samples are also collected and analyzed by other programs (USGS 1997; USGS 2011; Zhao et al. 2012). However, collecting discrete samples is expensive and time consuming. To address the challenges in monitoring water quality and quantity at a large scale, novel remote sensing techniques will be needed. Another challenge is the lack of observability caused by the interactions between resources. For example, in agriculture, pumping irrigational water requires energy. However, currently, there is no sensing technology to estimate the total energy required for agricultural purposes. Thus, new spatial data models will be required when such observation data is missing.

Finally, crowdsourcing should not be neglected. Advances in mobile technology such as smartphones, location-based social networks, etc. provide tremendous opportunities for collecting FEW data via crowdsourcing, also called volunteered geographical information (VGI) (Okolloh 2009; Butler 2013; Shekhar et al. 2015b). For example, "mWater," a mobile application for water quality monitoring, leverages mobile technology and an open data sharing platform for water safety testing and allows volunteers to easily find the safest water sources near them (MWater 2013). Such data collected from VGI should be incorporated to the data collected from other sources. Thus, the data heterogeneity (e.g., data coming from different sources, with different accuracies and in different spatial and temporal resolutions), which prohibits the integration of FEW observation data across different platforms, should be addressed.



a. Surface water b. Ground water

Fig. 8 Water source observation locations (USGS 2011)

Spatial data management

The need for specialized spatial data management tools emerged due to the wide variety and amount of the data generated by remote sensing, ground sensors, GNSS, and other spatial data collection tools. Spatial database management systems were developed to address those issues caused by the use of traditional tools. Traditional database management systems are designed to do queries on one-dimensional data types (e.g., names, numbers, etc.). Therefore, they were not adequate for two-dimensional spatial data and such queries required extensive programming and long computational times. Moreover, spatial data types such as points, lines, and polygons could not be naturally represented. In contrast, Spatial Database Management Systems (SDBMS) support spatial data types using OGIS simple features (Consortium and Others 1999) and provide various spatial operations such as inside, outside, intersect, and distance (Shekar and Chawla 2003). SDBMSs support efficient access via spatial data structures such as R-trees. Due to the development of spatial database management systems spatial queries such as "Which regions of the country have low water levels?" or "Which regions in my state have enough water and soil nutrition to raise corn?" now can be easily processed. Moreover, a SDBMS provides a more natural way to represent spatial queries that allows users to spend less effort to structure their queries.

We envision that spatial data management tools may support efficient management of FEW data. Recent spatial computing advances in 3D modeling provide a more convenient representation of data collected from ocean and underground sensors (Heidemann et al. 2012), which was traditionally modeled by OGIS simple features in a 2D space. Novel spatial big data infrastructures provide a platform to manage and analyze large-scale spatial datasets (e.g., remote sensing imagery of the entire earth) in the cloud. For instance, Google Earth Engine (Google 2015), for the first time ever, provides efficient storage and computation of all kinds of remote sensing imagery of the entire earth surface over several decades in the cloud. Moreover, a cloud environment nurtures the development of volunteered geographical information from check-ins, tweets, geo-tags, and geo-reports. Finally, efficient support for spatial graph queries such as critical node and path computation can help enhance the resilience of FEW resources.

However, the FEW datasets are highly heterogeneous, since the data collection processes are for various purposes and in various formats and spatiotemporal resolutions (e.g., UAV imager at sub-meter resolution, Landsat images at 20- or 30-m resolution, MODIS at 250-m resolution), limiting the potential value of the data. Additionally, the various spatial scales of raster data cause the Modifiable Areal Unit problem (Openshaw 1984), where the same analytics method may produce different results under various scales. Spatial computing can help develop systematic data standards and data sharing protocols considering various FEW applications as a whole (e.g., Global Earth Observation System of Systems (Achache 2015), Nexus Observatory Platform (UNU-FLORES 2015). Figure 9 illustrates a recent effort namely the GEOSS (GEOSS 2015) platform towards a unified data management system to store and access FEW data from different sources including space-based systems, air-based systems, and land-based system, etc. GEOSS aims to produce a global public infrastructure that generates comprehensive, near-real-time environmental data, information, and analyses for a wide range of users. Collected data (by the GEOSS platform) will be used in different application domains including health, disaster management, weather services, energy, water and agricultural (food) production, climate studies, ecological studies, and biodiversity protection.

In order to develop a comprehensive data management framework to facilitate the interoperability on FEW nexus data across disciplines, several other technical challenges need to be addressed. First, many FEW datasets are collected from 3D Euclidean space (e.g., ocean data or subsurface data) or spatial network space (e.g., river networks) and often with the

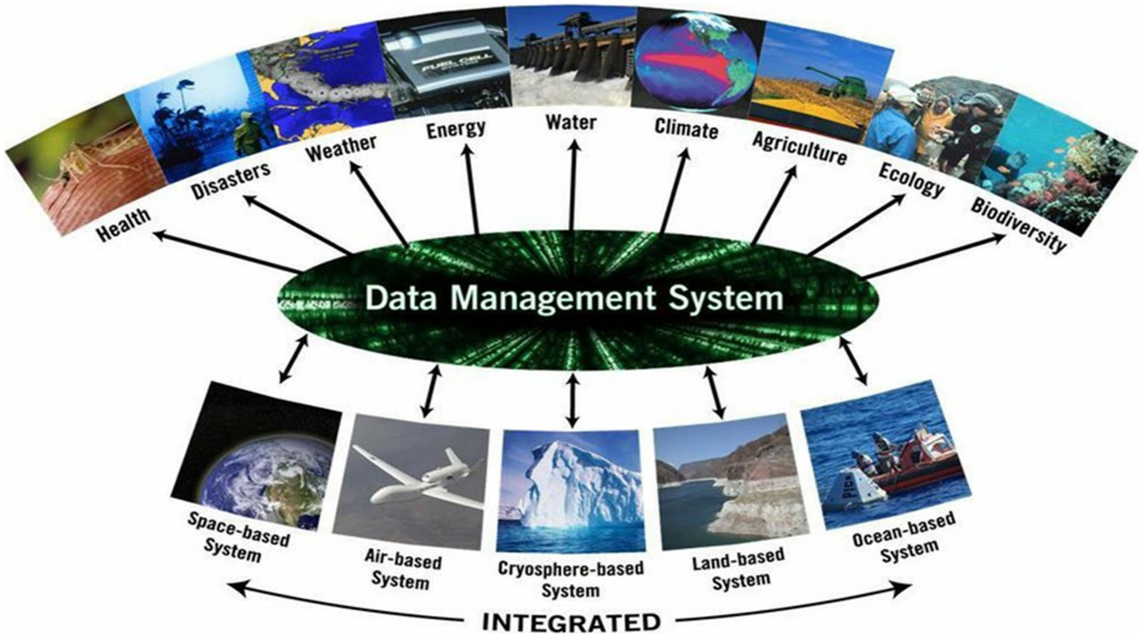


Fig. 9 An illustrative example of FEW data management from GEOSS (GEOSS 2015)

additional dimension of time, which requires novel data models and representations. Second, traditional spatial data management tools were designed to store and manage geometric and raster data but some FEW data are from volunteered geographic information (VGI) that often contains place-names and prepositions (e.g., near, in, at, along, etc.) instead of numerical coordinates (e.g., latitude-longitude). Therefore, there is a need for new methods to interpret these place-names as well as methods to clean data errors, evaluate trustworthiness, and avoid bias, etc. Finally, although there is a wide variety of spatial and spatiotemporal data already collected and managed by different groups and organizations, there is a lack of data sharing platforms and causing each institution or group to spend their efforts using only the data they have.

Spatial data mining

Spatial data mining is the process of discovering interesting and previously unknown, but potentially useful patterns from large spatial datasets (Kemp 2008). Due to the complex interactions between spatial data as well as the spatial correlations and relationships between locations, spatial data mining is a difficult task. For example, Tobler's first law of geography stating that, "Everything is related to everything else, but near things are more related than distant things" (Tobler 1970) should be taken into account by spatial statistics, which distinguishes it from traditional statistics. Spatial statistics (e.g., spatial point process, spatial autocorrelation, geostatistics) aims to overcome the unique challenges of applying traditional statistical models to geographic data, e.g., violation of independent and identical distribution assumption (Zimmerman and Stein 2010). Spatial statistics techniques are widely used for weather forecasting where data assimilation is required. In mining for energy production, spatial statistics techniques such as Kriging are also used for estimating the location for a rich ore (Ester et al. 1997). In agriculture, spatial statistics is used for designing zones for precision agriculture and agricultural census as well as delineating the management zones.

Advances in spatial statistics and spatial data mining may provide a data science approach for understanding the nexus of FEW resources. Traditionally, FEW systems have been studied via mechanistic process models. These have many advantages such as good interpretability, and the capability to make future projections. However, as observation data is being collected at much higher spatial and temporal resolutions, traditional mechanistic process models may be supported by these rich data to leverage the spatiotemporal contextual information that is required for the situational assessment of FEW resources. For example, previously, crop production used to be modeled and studied at a county or a state level. However, nowadays, precision agriculture allows analyzing crop health at the plot or subplot level.

Spatial data mining tools are widely used for precision agriculture tasks. For example, hotspot analysis in spatial data mining is used to determine the hotspots of locations where the soil has high nutrient or moisture levels to prevent applying more fertilizer or irrigation to these locations. Similarly, co-location pattern mining tasks are used to determine which combination of fertilizer and water makes the crops healthier and in which location of the field. In addition, spatial data mining tasks allow predicting future yield from a field. These yield projections help farmers make a crop-type decision for the next harvesting season. Also, these give more insights about the causes of low or high yields, best crop type for a specific type of soil and location in a field, etc.

Spatial data mining techniques may play a crucial role in providing a real-time computational analysis of the rich FEW datasets. Similar to precision agriculture but from a broader perspective, spatial data mining can identify previously unknown but potentially interesting patterns (e.g., spatiotemporal coupling or telecoupling, spatial hotspots, co-occurrences). In turn, the rich FEW data sources may improve the accuracy and timeliness of spatiotemporal predictions and spatial statistical approaches may help test the significance of these predictions. Similarly, spatial data mining tasks may give deep insights for future FEW events. By using spatial data mining techniques on the previous chokepoint events that happened in the past, it may help predict future FEW resource chokepoint events similar to weather forecasting. Moreover, spatial computing may help illustrate future events of either food, energy, or water resource risks (e.g., scarcity, environmental catastrophe) on a map (e.g., event type, location, and time) just like weather forecasts. We believe FEW chokepoint forecasting may help decision-makers to get the required precautions before chokepoint events happen.

However, significant challenges exist in utilizing spatial data mining techniques for analyzing the rich FEW data. These challenges include lack of tools for building 3D models and spatiotemporal network models (e.g., anisotropic and asymmetric spatial neighborhood), inability to simulate the decision-making process of policymakers, and difficulty of future projections when the assumption of stationarity does not hold. For example, agricultural decision-makers often use land use change monitoring (Brown et al. 2014) to manage water and land resources as well as supply chain modeling in a specific location (Min and Zhou 2002). However, spatial data mining approaches used for land change modeling tasks pose several problems. First, these spatial data mining tools often depend on the input data. Thus, when using sampling techniques, the output of these models may be sensitive to the sample of the input. Second, many spatial data mining and spatial statistics tools use a stationarity assumption. The stationarity assumption means that the model created in the training phase of the tool is assumed to be consistent over time. In other words, if the conditions change over time, the generated model may not reflect the actual case. For example, a model, which is created for the climate conditions of a specific agricultural field, may not reflect the present conditions of the field due to the climate change and therefore may cause wrong projections for the future. Thus, there is a need for tools that will adapt the model to the changes over time (i.e., real-time) (Geographical Sciences Committee 2014). In addition, many spatial data mining tools do not provide an interpretation of the results, which may cause users to misinterpret in some conditions.

Spatial data visualization

Thanks to the recent advances on spatial data visualization, detailed spatial information collected by remote sensing, census data, etc. is broadly accessible through the Virtual Globe applications. A few examples of such applications include Google Earth, NASA World Wind, Microsoft Bing Maps, Apple Maps, and UMN MapServer (Vatsavai et al. 2006). These applications are already widely used for visualizing environmental changes happening in different regions on Earth. People may also use them to contribute new information and enrich their applicability. In addition to the publicly available and free tools, more customizable and domain-specific tools are also available. For example, precision agriculture tools visualize many parameters on a field with different layers on a map (as illustrated in Fig. 10). By visualizing the soil properties and moisture levels as well as crop health, precision agriculture farmers can decide where to use different kinds of seeds. Moreover, such visualizations can be used for yield monitoring to determine the expected yield on different parts of the field.

Either domain specific as in precision agriculture or publicly available, such visualization tools allow interested individuals as well as policymakers to help understand the human activities and natural phenomena (e.g., earthquake, hurricane, drought, crop health) that may not be explicit without illustrating. For example, Fig. 11 shows the shrinkage of the Aral Sea due to extreme irrigation combined with drought. The Aral Sea was the fourth largest lake in the world in the 1960s, which had been fed by the Syr Darya and the Amu Darya rivers. However, in order to improve the agricultural use in the dry plains, Soviet officials diverted the water in these rivers for irrigation of cotton and other crops. Although the irrigation project was a success for agriculture, it devastated the Aral Sea. In this example, three remote sensing images taken on 1977, 1998, and 2010 shows the change of the Aral Sea basin in time (NASA 2012). This illustration shows the importance of the temporal dimension of visualizations as well as the devastating effects of trying to improve one resource without considering others.

We envision that spatial computing may help improve the visualizations of different variables of food, energy, and water resources similar to the layered design of precision agriculture maps that show different variables of a field. Recently, virtual globes applications start to provide visualization of the changes on the entire Earth over a long period of time (e.g., Google Time Lapse). Thus, similar tools that will be designed for FEW domain scientists may allow visualization of the interactions and interdependencies of FEW resources over time. In addition, we envision that such visualizations may be used with spatial data mining tools to provide not only historic records of FEW resources (as in Fig. 11), but also future scenarios at a global scale. An example from a single resource perspective, Famine Early Warning System Network (FEWSNET), visualizes possible

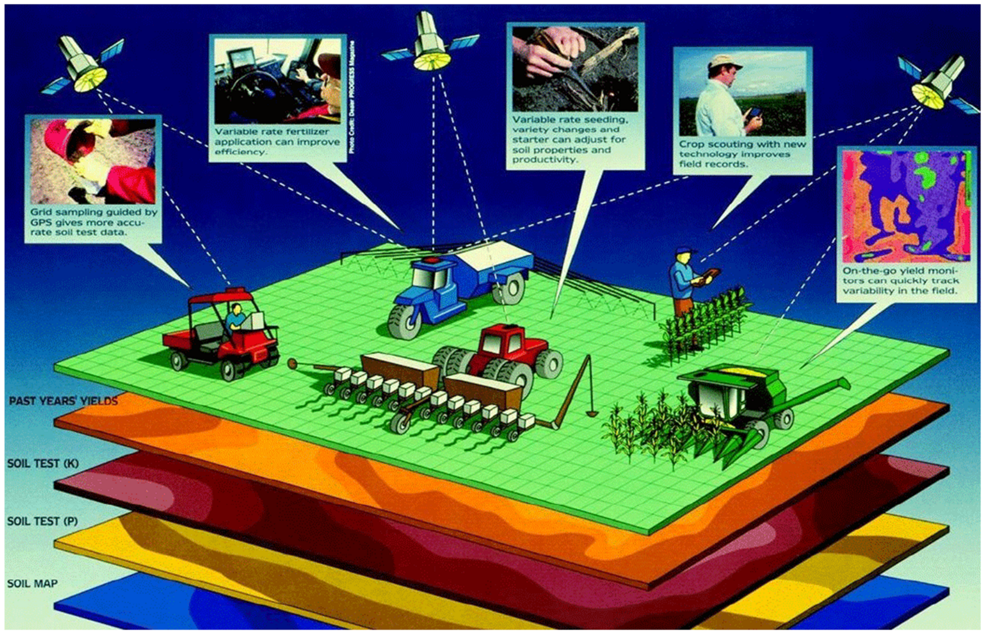


Fig. 10 Illustration of precision agriculture (Plant et al. 2000)

locations with food insecurity for short- and medium-term time periods (FEWSNET 2013) in order for policymakers to take required precautions. Similarly, future predictions and visualizations from the FEW nexus perspective (considering all three resources) may assist decision-making agencies to effectively demonstrate future effects of their policies.

However, visualizing the interactions between resources is more challenging than visualizing the layers of precision agriculture maps. First, precision agriculture applications are often in a limited space (i.e., farm, field). However, monitoring FEW resources will require global visualization tools. Secondly, precision agriculture applications collect data from all over the field with regular sampling rates in a relatively finer temporal resolution. However, due to inadequate FEW data collection on a global scale, FEW Nexus visualizations will require more sophisticated techniques to visualize the "uncertainty" about location, value, and quality of spatiotemporal information. Such tools should handle problems such as the lack of site-specific data and the limitations of estimation models that result in uncertainty when estimating water resource consumption. Finally, precision agriculture applications often use the Euclidean space and add each data as layers to this map, but interactions between FEW resources may happen in different spaces. For example, ocean and underground water data are often presented in a 3D Euclidean space, while surface stream flow data is in a spatial network space. Visualizing these water data in both Euclidean space and spatial network space is non-trivial. Finally, FEW visualization tools should also visualize the effects of other factors such as the migrations of populations due to economic reasons as well as the climate change to support a better understanding of FEW resources.

Spatial decision support

Spatial decision support systems use the previously described spatial data and spatial computing tools to help ease the

Fig. 11 The Aral Sea shrinkage started in the 1960s due to the extensive agricultural irrigation. From left to right, the remote sensing images were produced in 1977, 1998, and 2010. NASA (2012) Landsat top ten—a shrinking sea, Aral Sea. http://www.nasa.gov/mission_pages/landsat/news/40th-top10-aralsea.html

decision-making process for users. Currently, these tools are used widely by policymakers, governments, and organizations for their operational and strategic planning tasks. For example, a grocery chain company may use such a tool to determine how many stores it needs and which locations to install its new branches. An energy distribution company may use spatial decision support systems to determine the peak electricity demand hours and adapt electricity production accordingly. Similarly, a government agency making environmental plans may get assistance of spatial decision support systems for making land use decisions.

In Precision Agriculture, spatial decision support systems often use the collected spatial and spatiotemporal datasets to model the present conditions and make decisions using some projections of future events. For example, detailed observation data on crop fields collected by drones or ground sensors are used to monitor crop health and support decisions on how much water and fertilizer to apply and to which plots or subplots, in order to minimize water or energy consumption while maximizing the production (McBratney et al. 2005). In addition to the reactions and assistances for short-term changes in the field, spatial decision support systems may also give future predictions such as the projected amount of yield and possible alternative types of crops for a next year.

We envision that spatial computing may provide useful insights as well as alerts and future predictions for FEW resources using the Nexus Dashboard analogy as described in Fig. 4. A Nexus Dashboard system, used as a decision support tool, may improve the visibility and timely detection of the food, energy, and water resources. For example, future problems similar to the Aral Sea shrinkage problem may be prevented by the dashboard analogy. Nexus Dashboard may improve the mapping and visualization of historic trends, future projections, and it may visualize or model the resources even when observations are scarce (e.g., groundwater). For example, although the Ogallala Aquifer observations are scarce due to the lack of underground sensing methods, future depletion/water scarcity risks due to extreme irrigation may be prevented by spatial modeling methods, previous chokepoint events (i.e., Aral Sea shrinkage) as well as future projections in the Nexus Dashboard. These future projections may also produce alerts that will warn for unintended consequences such as the fertilizer run-offs causing fish dead zones in the gulf (as shown in Fig. 5). In addition, a global Nexus Dashboard analogy may help consensus building and participative planning tasks to handle the challenges caused by fragmented spatial data.

However, spatial decision support systems need to address several challenges before users can fully realize their potential as a Nexus Dashboard to monitor FEW resources. For example, FEW decision support systems should be able to support users in the event that FEW resources cause spatial externalities. For example, farmers who pump the underground water supplies to irrigate their field may cause a spatial externality where pumping at one farm may affect the water levels underground and thus affect other nearby farms. This will cause more than usual energy consumption for pumping/irrigation purposes as well as risk drought in neighboring farms. Such externalities are often difficult to observe and modeling and creating future predictions and thus taking the required precautions to prevent such problems in future is a difficult task. These externalities may also have more complicated consequences in other resources, which require domain users to determine the interconnections between FEW resources. However, due to the "uncertainty" of interactions, such task is often hard without taking all resource externalities as well as interrelations into account. Despite being widely used, some current spatial decision support techniques (i.e., supply chain relocation, landscape design, precision agriculture) may also face challenges when they are considered under a global Nexus Dashboard analogy. For example, many local agencies, not even countries, are still lacking a supply chain relocation strategy to prevent unnecessary energy consumption for moving and processing the produced foods from one location to another. Another example is that a country may have water scarcity and use desalination (requiring high amounts of energy) to produce clean water for irrigation of agricultural goods, whereas another may have enough clean water for agriculture but not enough energy for public consumption. Such a problem may often be hard to solve in a global level (between countries) with current practices (e.g., virtual water trading) due to the conflicting national interests of countries. However, spatial decision support systems may help model, project, and predict the resources and help decision-makers to create better future plans.

Summary

The food, energy, and water (FEW) nexus framework considers these three inextricable resources from a system of systems perspective. The main goal of the FEW nexus is to reduce unintended resource scarcities by understanding, appreciating, and visualizing the interconnections and interdependencies in the FEW resources at local, regional, and global levels. The FEW nexus approach aims to achieve a resource sustainability and availability by applying the nexus framework on a local level of decision-making and also a regional and global level of policymaking processes.

National and international agencies have recently started to focus on the sustainability and availability of food, energy, and water resources from a FEW nexus perspective. These initiatives mostly focus on the problem from a pure physical science perspective. For example, a 2014 report by the National Science Foundation Mathematics and Physical Sciences Advisory Committee identified key areas where physical science could address the FEW nexus such as developing desalination technologies to increase sustainable water supplies for agriculture, and improving crop protection via bio-pesticides and genetic techniques. No doubt, FEW nexus challenges cannot be addressed without physical sciences. Overlooked—or perhaps taken for granted—in these reports is that spatial computing and technologies may help domain scientists achieve their goals for the FEW nexus.

In this paper, we present a spatial computing vision to improve the efficiency of the FEW nexus thinking. We envision a spatial computing tool called the Nexus Dashboard, which may offer insights into the interactions and interdependencies of FEW nexus as well as provide future projections and early warnings to domain scientists in addressing FEW nexus challenges. Individual components of the Nexus Dashboard are described using the spatial data lifecycle components, including spatial data collection, data management, data mining, and visualization tools. We also identified spatial computing challenges arising from the FEW nexus within each component.

Acknowledgments This material is based upon work supported by the National Science Foundation under Grant Nos. 1029711, IIS-1320580, 0940818, and IIS-1218168; U.S. DoD under Grant No. HM1582-08-1-0017; and the University of Minnesota via U-Spatial. We would like to thank Kim Koffolt and the members of the University of Minnesota Spatial Computing Research Group for their comments.

References

Achache J (2015) Modeling the Global Earth Observation System of Systems. Proc 2006 Inst Ind Eng Annu Conf 12:14946

Allan JA (2003) Virtual water—the water, food, and trade nexus. Useful concept or misleading metaphor? Water Int 28:106–113. doi:10.1080/02508060.2003.9724812

Andrews-Speed P, Bleischwitz R, Boersma T, et al. (2012) The Global Resource Nexus. The Struggles for land, energy, food, water, and minerals. Routledge, London

Bazilian M, Rogner H, Howells M, et al. (2011) Considering the energy, water and food nexus: towards an integrated modelling approach. Energy Policy 39:7896–7906. doi:10.1016/j.enpol.2011.09.039

Brown DG, Band LE, Green KO, et al. (2014) Advancing land change modeling: opportunities and research requirements. National Academies Press, Washington DC

Butler D (2013) When Google got flu wrong. Nature 494:155–156. doi:10.1038/494155a

Campbell JB, Wynne RH (2011) Introduction to remote sensing, Fifth edn. The Guilford Press, New York(ISBN: 160918176X)

Consortium O et al. (1999) OpenGIS simple features specification for SQL. OpenGIS Proj Doc 99(49):49–99

Ester M, Kriegel H, Sander J (1997) Spatial data mining : a database approach. In: Proceedings of the 5th International Symposium on Advances in Spatial Databases. Springer, Berlin Heidelberg, pp. 47–66

FEWSNET (2013) Nutrition|Famine Early Warning Systems Network. http://www.fews.net/sectors/nutrition. Accessed 8 Jan 2016

Flammini A, Puri M, Pluschke L, Dubois O (2014) Walking the nexus talk: assessing the water-energy-food nexus in the context of the sustainable energy for all initiative

Geographical Sciences Committee. (2014) Advancing land change modeling: opportunities and research requirements. National Academies Press, Washington DC

GEOSS (2015) GEOSS Portal. Website GEO (gr. Earth Obs.)

GNSS (2011) GNSS Systems Reports

Google (2015) Google Earth Web Site. https://www.google.com/earth/explore/products/. Accessed 1 Jan 2015

Healy RW, Alley WM, Engle MA, McMahon PB, Bales JD (2015) The water-energy nexus: An Earth Science Perspective (No. 1407). US Geological Survey, Chicago

Heidemann J, Stojanovic M, Zorzi M (2012) Underwater sensor networks: applications, advances and challenges. Philos Trans R Soc A Math Phys Eng Sci 370:158–175. doi:10.1098/rsta.2011.0214

Hellegers P, Zilberman D, Steduto P, McCornick P (2008) Interactions between water, energy, food and environment: evolving perspectives and policy issues. Water Policy 10:1. doi:10.2166/wp.2008.048

Hoekstra a. Y, Hoekstra a. Y (2003) Virtual water trade. Int Expert Meet Virtual Water Trade 12:1–244

Hoff H (2011) Understanding the nexus. Background paper for the Bonn2011 Conference: the water, energy and food security nexus. Security 1–52

Kemp K (2008) Encyclopedia of geographic information science. SAGE Publications (ISBN 1412913136)

Lillesand TM, Kiefer RW, Chipman JW (2009) Remote sensing and image interpretation. John Wiley & Sons, Chichester

Liu J, Mooney H, Hull V, et al. (2015) Systems integration for global sustainability. Science (80-) 347:1258832–1258832. doi:10.1126/science.1258832

Lundy J, Bowdish L (2014) The energy-water-food neuxs: insights for the business community. NEXUS Platf. - Water Energy Food Secur. Nexus - NEXUS Resour

McBratney A, Whelan B, Ancev T, Bouma J (2005) Future directions of precision agriculture. Precis Agric 6:7–23. doi:10.1007/s11119-005-0681-8

Melo MT, Nickel S, Saldanha-da-Gama F (2009) Facility location and supply chain management—a review. Eur J Oper Res 196:401–412. doi:10.1016/j.ejor.2008.05.007

Min H, Zhou GG (2002) Supply chain modeling: past, present and future. Comput Ind Eng 43:231–249. doi:10.1016/S0360-8352(02)00066-9

Mohtar RH, Daher B (2012) Water, energy, and food: the ultimate nexus. Encyclopedia of Agricultural, Food, and Biological Engineering

MWater (2013) mWater. http://www.mwater.co/. Accessed 9 Jan 2016

NAP (1997) Precision agriculture in the 21st century. National Academies Press, Washington, D.C.

NAS (2012) Global navigation satellite systems: report of a Joint Workshop of the National Academy of Engineering and the Chinese Academy of Engineering. The National Academy Press(ISBN 978–0-309-22275-4)

NASA (2012) Landsat top ten—a shrinking sea, Aral Sea. http://www.nasa.gov/mission_pages/landsat/news/40th-top10-aralsea.html

NIC (2015a) Continuity of NASA Earth observations from space. National Academy Press, Washington, DC

NIC (2015b) NASA Space Technology Roadmaps (2015 Draft)

NRC (1997) Precision agriculture in the 21st century: geospatial and information technologies in crop management. The National Academies Press, Washington, DC

NRC (2014) Opportunities to use remote sensing in undestanding permafrost and related ecological characteristics: report of a workshop. The National Academies Press(ISBN: 978–0-309-30121-3)

NSF (2014a) Geospatial data project puts major issues on the map. http://www.nsf.gov/discoveries/disc_summ.jsp?cntn_id=132971&WT.mc_id=USNSF_1. Accessed 8 Jan 2016

NSF (2014b) Food, Energy and Water: Transformative Research Opportunities in the Mathematical and Physical Sciences, Mathematical and Physical Sciences Advisory Committee - Subcommittee on Food Systems, July 2014. www.nsf.gov/mps/advisory/mpsac_other_reports/nsf_food_security_report_review_final_rev2.pdf

NSF (2015) Dear colleague letter: SEES: interactions of food systems with water and energy systems. \url{http://www.nsf.gov/pubs/2015/nsf15040/nsf15040.jsp}

Okolloh O (2009) Ushahidi, or "testimony": Web 2.0 tools for crowdsourcing crisis information. Particip Learn Action 59:65–70

Openshaw S (1984) The modifiable areal unit problem. Geo Books, Norwich

Parkingson B, Spilker J (1996) Global positioning system: theory and applications. Aiaa

Pierre Guillibert (2015) FEW nexus resource platform. http://www.water-energy-food.org/. Accessed 8 Jan 2016

Plant RE, Pettygrove GS, Reinert WR (2000) Precision agriculture can increase profits and limit environmental impacts. Calif Agric 54:66–71. doi:10.3733/ca.v054n04p66

Rabalais NN, Turner RE, Wiseman WJ (2002) Gulf of Mexico hypoxia, A.K.A. "The Dead Zone.". Annu Rev Ecol Syst 33:235–263. doi:10.1146/annurev.ecolsys.33.010802.150513

Scott C, Pierce S a, Pasqualetti MJ, et al. (2011) Policy and institutional dimensions of the water-energy nexus. Energy Policy 39:6622–6630. doi:10.1016/j.enpol.2011.08.013

Scott CA, Kurian M, Wescoat JL Jr. (2015) The water-energy-food nexus: enhancing adaptive capacity to complex global challenges. Governing the nexus. Springer International Publishing, Switzerland, pp. 15–38.

Shekar S, Chawla S (2003) Spatial databases: a tour. In: Spat. Databases A Tour. http://www.spatial.cs.umn.edu/Book/slides/. Accessed 8 Jan 2016

Shekhar S, Chawla S, Ravada S, et al. (1999) Spatial databases—accomplishments and research needs. Knowl Data Eng IEEE Trans 11:45–55. doi:10.1109/69.755614

Shekhar S, Feiner S, Aref WG (2015a) From GPS and virtual globes to spatial computing—2020. Geoinformatica 19:799–832. doi:10.1007/s10707-015-0235-9

Shekhar S, Feiner SK, Aref WG (2015b) Spatial computing: accomplishments, opportunities, and research needs. Commun ACM 59:72–81. doi:10.1145/2756547

Tobler W (1970) A computer movie simulating urban growth in the Detroit region. Economic geography 234–240

U.S. Dept.of State (2015) Fulbright Water-Energy-Food Nexus Workshop. http://www.state.gov/p/sca/rls/rmks/2015/237429.htm. Accessed 8 Jan 2016

UNU-FLORES (2015) Nexus Observatory Platform Web Site

USGS (2011) USGS Groundwater Watch. http://groundwaterwatch.usgs.gov/AWLSites.asp?S=302416087505501&ncd=. Accessed 9 Jan 2016

USGS (1997) U.S. GEOLOGICAL SURVEY Open-File Report 97–121

Vatsavai R, Shekhar S, Burk T, Lime S (2006) UMN-MapServer: a high-performance, interoperable, and open source web mapping and geo-spatial analysis system. Geographic, Information Science, In, pp. 400–417

Webber M (2015) Energy, water and food problems must be solved together. Sci Am 312:5

Wright BD (2009) The Food Price Crisis of 2007/2008 : FAO food outlook Glob Mark Anal Retrieved 1–11

Zainuddin M, Kiyofuji H, Saitoh K, Saitoh SI (2006) Using multi-sensor satellite remote sensing and catch data to detect ocean hot spots for albacore (*Thunnus alalunga*) in the northwestern North Pacific. Deep Res Part II Top Stud Oceanogr 53:419–431. doi:10.1016/j.dsr2.2006.01.007

Zhao D, Jiang H, Yang T, et al (2012) Remote sensing of aquatic vegetation distribution in Taihu Lake using an improved classification tree with modified thresholds. Journal of environmental management 95(1):98–107

Zimmerman DL, Stein M (2010) Classical geostatistical methods. Handbook of spatial statistics, pp. 29–44. Chapman & Hall/CRC, Boca-Raton