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Ecosystem-based adaptation

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Human well-being is inextricably linked to ecosystem processes. The success of societies is predicated on past, current, and future states of the natural environment, and humans have struggled to adapt their systems to changes in ecosystem processes for millennia. Periods of unsuccessful adaptation have led to societal distress (Parker 2013). Functioning ecosystems and the services they provide may, in many cases, supply humans with the best opportunities to adapt under climate change.

Ecosystem services are the benefits that people obtain from ecosystems. Although any classification scheme belies the interconnectedness of these services, they are most frequently identified as supporting services that underpin all others (e.g., primary production, nutrient cycling), provisioning services (e.g., providing food, fibers, natural medicines), regulating services (e.g., climate regulation, water purification), and cultural services (e.g., recreational opportunities, spiritual importance; Millennium Ecosystem Assessment 2005). Some services can be replaced by technology at low cost whereas other large-scale services have no feasible substitutes. Biodiversity is a contributing factor to sustainable delivery of these services, and redundancy in ecosystem functionality that accompanies healthy, biodiverse ecosystems further ensures both natural and human system stability.

Ecosystem-based adaptation (EbA) strategies "harness the capacity of nature to buffer human communities against the adverse impacts of climate change through the sustainable delivery of ecosystem services" (Jones et al. 2012). EbA leverages – and aims to protect – ecosystem services to build adaptive capacity, resistance, and resilience into human systems. EbA can complement 'soft' adaptation approaches such as livelihood diversification or replace 'hard' adaptation approaches, which use specific technologies and capital goods and are often engineered, infrastructure-based interventions (Jones et al. 2012).

Like ecosystem services, EbA approaches transcend rigid categorization – many overlap and reinforce each other. Here, for illustrative purposes, we focus on five broadly defined environments: agricultural landscapes, urban areas, coastal zones, freshwater, and forests. We identify several ecosystem services generated in each environment, how climate change has and will impact these services, and potential EbA strategies to maintain them. We also identify related EbA co-benefits and alternative interventions. We conclude with a discussion of both the opportunities and potential pitfalls of EbA.

AGRICULTURE

Climate change is expected to lengthen growing seasons, alter rainfall patterns, increase the frequency of extreme weather events, and shift both pest and pest-predator ranges (Wheeler and von Braun 2013). To adapt to these changes, production farmers (as opposed to subsistence farmers) may change seed varieties, adjust irrigation and fertilizer amounts, and modify planting and harvesting dates.[1] Farmers may also leverage ecosystem services to maintain yields in the face of climate change – for example, by increasing soil biodiversity, maintaining pollinator habitat, and ensuring sustainable water provisioning.

Farmers can improve yields by increasing biodiversity in their soils. For example, wheat yield in the Scania region of Sweden increased by 3.2 Mg ha^{-1} when soil organic carbon (SOC) content – a proxy indicator of soil biodiversity (de Vries et al. 2013) – was increased from 7.9 g kg^{-1} of soil to 19 g kg^{-1} of soil (Brady et al. 2015). An examination of the relationship between 2009 crop yield, growing season weather, and SOC across all of Europe for multiple crops corroborates the impact SOC can have on yields at the margin, especially when growing season weather is not ideal (see shaded leaf nodes in Figure 1).

[1] In some cases the optimal response to climatic changes will be to change the types of crops planted. However, national agriculture policies may make such welfare-enhancing crop swaps difficult. For example, many national biofuel policies that subsidize maize or sugar production may incentivize farmers to continue planting crops not best suited for the emerging climate. Unless subsidy policies are sensitive to climate change, regulatory inflexibility is likely to make global agriculture less resilient to climate change.

Activities that increase SOC, such as adding manure to the soil and including cover crops in rotations (Alvarez 2005), generate both direct and opportunity costs (e.g., a rotation of cover crops means no marketable yield that year). If, however, the increase in yield from enhanced SOC outweighs costs, farmers will have an incentive to increase SOC. Furthermore, the societal co-benefits generated by greater SOC levels, including reduced need for chemical fertilizers (and therefore reduced run-off and eutrophication) and reduced atmospheric CO_2 concentrations, may make it optimal for governments to subsidize SOC investments.

Increasing pollination capacity is another EbA strategy to buttress food production from adverse climate change impacts. Globally, 75% of all human-consumed crops require insect pollination (Klein et al. 2007) yet widespread declines in pollinator abundance, mostly due to habitat conversion, are compromising the quality and quantity of food production. Ensuring pollination services requires coordinated action across agricultural landscapes, as ecosystem services mediated by mobile organisms like pollinators are impacted by management at scales larger than individual farms (Cong et al. 2014). Economists have demonstrated that small payments encourage farmers to provide pollinator habitat, when accompanied by larger fines for any subsequent habitat destruction (Cong et al. 2014).

As global demand for food grows and rainfall patterns change, farmers will increasingly look to irrigation as an adaptation measure. For example, northern China is projected to become drier while southern China gets wetter (Piao et al. 2010). Such changes will force northern farmers to adopt more drought-tolerant crops or, less likely, devise ways to transport water from south to north (Piao et al. 2010). In other places, climate change may cause increased precipitation in the winter and decreased precipitation during the growing season. Storing non-growing-season precipitation in networks of constructed retention ponds and restored wetlands could ensure water availability during increasingly dry growing seasons (Baker et al. 2012) while also reducing flood risk and providing wildlife habitat.

Farmers of agroecosystems, subsistence farmers, and small-scale farmers generally tend to rely much more heavily on ecosystem services to manage uncertainty and environmental variability than do large-scale production farmers (Tengö and Belfrage 2004). Grazing animals on crop fields and including grasses in crop rotations are two tactics still widely used by subsistence farmers to maintain SOC and biodiversity. Intercropping and maintenance of pollinator and natural pest habitat also help maintain acceptable yields. Although these agricultural systems are much more sustainable than the high-yield systems described above, their low productivity means they will not contribute significantly to global food supplies. Instead, if the global agriculture system is to become more resilient to climate change, the more input-intensive farmers will have adopt agroecosystem techniques that are compatible with high-yield farming.

URBAN AREAS

According to the United Nations (2014), 66% of the world's population will live in urban areas by 2050, meaning the majority of the world's people will directly experience climate change and attempt to adapt to it in the urban environment. Warmer temperatures will exacerbate the urban heat island (UHI) effect, while the frequencies of extreme weather events are expected to increase in urban areas. Extreme heat and precipitation events in cities increase human mortality rates and hamper the ability of infrastructure to perform adequately (IPCC 2014). For many coastal cities, sea-level rise (SLR) and storm surge are other climate change consequences to be addressed. (We address SLR management specifically in the coastal-zone section.) Green infrastructure and urban greenspace are two related EbA approaches that can be used to address many of these heat and water management-related issues.

Green infrastructure alternatives to the hard or 'grey' infrastructure typically used for stormwater management (e.g., drains, pipes) include green roofs, bio-swales, rain gardens, and constructed retention ponds and wetlands. The vegetation and soils associated with green infrastructure intercept precipitation and reduce the rate and volume of runoff (Gill et al. 2007). For example, a project in Seattle, Washington that included bio-swales, retention ponds, and a series of stepped pools retained 99% of wet season runoff (Horner et al. 2004). Similarly, a review of green roofs in German cities showed that intensive green roofs (with substrate >150 mm) could retain 75% of annual runoff (Mentens et al. 2006). In other words, green infrastructure can mitigate urban flooding by storing some of the excess water created by a storm. Further, any urban drought after an extreme precipitation event can be alleviated by the slow release of this excess water.

Ground and roof-top plantings in lieu of conventional dark materials and pavement reduces the UHI in general and the mortality impact of a heat wave specifically. Alternatively, 'white' and 'cool' roofs or even lighter-colored pavements that have higher albedo can reduce the UHI (Solecki et al. 2005) and the effects of heatwaves, though these approaches do not moderate stormwater runoff. Co-benefits of green infrastructure include water quality improvements due to filtration of natural pollutants and a reduction of water temperatures, aesthetic values of plantings, the potential for wildlife and pollinator habitat provisioning, and opportunities for small-scale urban agriculture.

Expanding and conserving existing urban greenspaces in and around cities – from pocket parks to vegetated corridors to protected forests – provide myriad ecosystem services and inherently entail EbA. Forested lands and street trees increase evaporative cooling and shade pavement, which help reduce the magnitude of the UHI, the impacts of heat waves, as well as energy consumption (e.g. for air conditioning; Parmova et al. 2012). For example, adding just 10% green cover to urbanized parts of Greater Manchester (U.K.) is projected to keep maximum summer surface temperatures at 29°C in the 2080s, compared to 32°C with current cover and 35°C with a 10% loss of green cover (Gill et al. 2007).

Restoring native species or planting drought-resistant species or hybrids can help ensure urban tree health while promoting biodiversity in plantings helps to prevent outbreaks of species-specific diseases and pests (Alvey 2006), particularly if urban trees are already experiencing climate-related stress. Co-benefits of increased greenspaces, especially urban forests, include carbon sequestration, improved air quality, psychological benefits, and opportunities for recreation in addition to other benefits enumerated above and in the forest discussion below.

COASTAL ZONES

Coastal and marine ecosystems provide a diversity of benefits. Fish and shellfish are important sources of sustenance and protein, and many coastal habitats protect infrastructure from storm surge and offer opportunities for recreation and aesthetic enjoyment. However, ocean acidification and warming are leading to shifts in the distribution of economically and ecologically important ecosystems and species while more frequent and intense storms increase the threat to coastal infrastructure (IPCC 2014). Conserving existing ecosystems, restoring degraded ones, and pursuing integrated management to reduce the cumulative risks from local stressors have the potential to enhance and maintain the functioning of coastal and marine ecosystems and the benefits they provide (Ruckelshaus et al. 2014). Below we discuss these EbA strategies in light of two important services – coastal storm protection and fisheries production.

Rising seas and potential increases in the intensity and frequency of storms pose risk to the 200 million people living in coastal regions worldwide (IPCC 2014). By attenuating waves and storm surge, coastal and marine ecosystems such as wetlands, coral reefs, and coastal forests can help reduce the impacts of such hazards (Shepard et al. 2011, Arkema et al. 2013). Conserving existing habitats and restoring degraded ones in regions with low-lying sandy and muddy coastlines (e.g., the east and gulf coasts of the U.S.) may effectively halve the number of people at high risk under climate change (Arkema et al. 2013). Funded by the U.S. federal government in the wake of Hurricane Sandy, several innovative projects involve building reefs to serve as 'natural breakwaters' to attenuate waves and reduce erosion while providing habitat for fish, shellfish and lobsters[2]. Leveraging ecosystems for coastal defense is often less costly to implement and maintain than hard infrastructure approaches including seawalls and levees (Jones et al. 2012).

Increasing ocean temperatures and changing water chemistry are disrupting the delivery of marine food and the livelihoods that facilitate this service (Ruckelshaus et al. 2014, Pinsky and Mantua 2014). For example, in the Northwest Atlantic, 24 out of 36 commercially exploited fish showed significant range (latitudinal and depth) shifts between 1968–2007 due to warming water (Nye et al. 2009). Changes in water chemistry affect the calcification rates of marine organisms (IPCC 2014), many of which are an important food source (e.g., oysters) or provide important nursery and adult habitats for fishes (e.g., corals). Coral conservation is particularly challenging in tropical systems where pollution, sedimentation, and unsustainable fishing stressors have not been addressed as successfully as in other parts of the world (Ruckelshaus et al. 2014). Efforts such as the multi-lateral Coral Triangle Initiative draw on ecosystem-based fisheries management and marine protected areas (MPAs) to safeguard biodiverse sites and sustain fish stocks to ensure food security in coastal areas[3]. Although alternative approaches to marine food production such as aquaculture

[2] http://www.rebuildbydesign.org/
[3] http://www.coraltriangleinitiative.org/

may offset some climate impacts on natural systems, these alternatives comes with risks of disease, habitat destruction, and pollution (Ruckelshaus et al. 2014).

Conservation, restoration, and integrated management of coastal and marine ecosystems have numerous co-benefits. Seagrasses and mangroves sequester carbon, such that degradation and conversion of these systems globally releases 0.15–1.02 Pg CO_2 annually and result in damages of $US 6-42 billion annually (Pendleton et al. 2012). Healthy coastal and marine ecosystems also provide tourism opportunities and support livelihoods in this sector. Given these additional co-benefits, EbA approaches are often superior to other options, but they do have their challenges. In the case of coastal protection services, perceptions of risk can be higher with green infrastructure than built systems and thus challenging to implement. Likewise, fisheries management can require coordination among many entities, making it particularly challenging.

FRESHWATER

Climate change is projected to substantially and nonlinearly impact surface water and groundwater resources. These impacts are likely to progress more quickly in heavily populated areas (Gerten et al. 2013). Geographic and temporal shifts in precipitation regimes will interact with changing temperatures to create more prolonged drought or, conversely, flooding associated with extreme weather events (IPCC 2014), impacts that will be felt most acutely in heavily populated areas (Gerten et al. 2013).

Traditional flood management strategies, such as straightening river channels and building dikes and levees, are vulnerable to failure and largely pass potential flooding problems downstream. EbA strategies for reducing the impact of floods enable excess water to spread into side channels and beyond river banks where it slows and infiltrates soils, thereby reconnecting rivers with floodplains, and holding excess water in natural areas above population centers (Palmer et al. 2009). Stream and riparian restoration that increases large woody debris, structural habitat, and channel complexity encourages incised channels to aggrade (Palmer et al. 2009) and improves overall ecosystem health (Beechie et al. 2010). Beyond the stream channel, afforestation and reforestation increase evapotranspiration and can prolong snow cover, thereby reducing downstream flooding by up to 54% in drier areas and 15% in more humid areas, as demonstrated in four South American case studies (Trabucco et al. 2008). These approaches also increase soil moisture and groundwater recharge, thereby providing direct benefits for agriculture, facilitating downstream groundwater withdrawals, and reducing fire risk (Postel and Thompson 2005), among other forest-related co-benefits identified in the forest discussion below.

It is likely that climate change will further reduce water availability in areas currently suffering from water scarcity (IPCC 2014). Indeed, 1.3 billion people already live in water-scarce regions, and global warming of 2°C, 3.5°C, and 5°C are projected to expose an additional 8%, 11%, and 13% of the world population to greater water scarcity, respectively (Gerten et al. 2013). Beyond the problem of limited water for direct human consumption and agricultural purposes, water shortages may result in habitat loss for pollinators and other species of economic importance, increased threat of forest fires, and saltwater intrusion into over-drawn aquifers. Substantial efficiencies can be achieved in water use by adopting practices such as upgrading leaky water delivery systems, recycling waste water, and implementing more efficient agricultural practices (IPCC 2014).

Some of these solutions, however, may be prohibitively expensive and will offer little benefit if natural ecosystems and processes that augment or ensure water provisioning are not protected. As noted in the forest discussion, forest ecosystems are critical for the sustainable water delivery to over a third of the world's largest cities (Dudley and Stolten 2003). The protection of high-elevation wetlands and peatlands – such as the Andean bofedales – may be critical for the persistence of pastoral native communities in otherwise inhospitable environments; these fragile ecosystems are extremely sensitive to climatic changes (Squeo et al. 2006). Elsewhere, natural and constructed wetlands have been effectively used to retain surface water, recharge groundwater, and filter out pollutants; these systems can be more cost-effective and permanent than treatment facilities (Jones et al. 2012). Natural ecosystem engineers like beavers have been used to increase water retention and hydrologic stability through their creation of wetland complexes where wetlands would otherwise not exist. Although these EbA strategies are promising, realization of large-scale adaptation goals will require watershed assessments, long-term planning, synchronization of multiple cross-watershed entities, and close coordination with local populations to ensure stakeholder buy-in.

FORESTS

Humans derive many benefits from forests, from local to global scales. For example, one-third of the world's largest cities obtain a significant proportion of their drinking water directly from protected forests (Dudley and Stolten 2003). Conserving the biodiversity and processes of forest ecosystems and restoring the integrity and resilience of degraded ones are primary strategies for leveraging forests for climate change adaptation.

Restoration of coastal forests can minimize inland flooding and coastal storm-surge events, which are projected to become more frequent and greater in magnitude (IPCC 2014). From riparian forests to coastal mangrove forests, vegetation structure physically slows water flow, attenuates wave and tidal energy, and stores water through plant uptake, thus minimizing the threat of flooding. Indeed, fewer lives were lost in coastal communities with healthy mangrove forests than those without during the 2004 Indian Ocean tsunami (Das and Vincent 2009). Mangroves additionally capture nutrient-rich sediments in their root structures and maintain important habitat for birds, fish, and other marine species. Similarly, through shading and inputs of in-stream large woody debris, riparian forests maintain thermal refugia for temperature sensitive species, such as spawning salmon (Palmer et al. 2009). Although conservation and restoration of these natural coastal and inland buffering systems can require multi-scale and cross-sector coordination for successful maintenance, the co-benefits and cost savings compared to dams, levees, and other shoreline defense approaches can be considerable (Jones et al. 2012).

As described above, changes in precipitation regimes may necessitate greater water storage capacity and filtration – services that forest vegetation and soils afford. Already, many municipalities have realized significant cost savings from investing in the forested watershed conservation (e.g., the Catskill-Delaware watershed north of New York City) instead of water purification infrastructure, which requires initial capital and continued maintenance (Jones et al. 2012). Elsewhere, tropical montane cloud forests are prime candidates for continued conservation in a changing climate, as they play an important role in water supplies: water vapor condenses on foliage and flows into streams, significantly augmenting water availability from rainfall in drier, low-elevation areas (Postel and Thompson 2005). By contrast, deforestation throughout Amazonia increases run-off and water discharge at local scales and – as demonstrated with simulations – impacts the water balance, hydrology, and surface temperatures across the entire Amazon Basin and likely globally (Foley et al. 2007).

Along with deforestation and degradation, a major threat to ecosystem services from forests are forest fires. From Australia to North America, synergistic effects of climate change-related drivers are fueling more catastrophic forest fires. For example, drought conditions in the western U.S. are interacting with increasingly widespread mountain pine beetle outbreaks as the beetles' range expands. Combined with a management legacy of fire suppression and selective harvesting, these forest stressors can lead to larger, more severe wildfires. Managers in fire-prone areas can ameliorate this stress and reestablish system resilience by restoring the patterns and processes typical of healthy, fire-prone forests – for example, through thinning and prescribed burning to reduce fuel loads and minimize the threat of catastrophic fires (Postel and Thompson 2005). This ecosystem-based approach in turn decreases the tremendous costs associated with firefighting – both in dollars and lives.

Beyond the ways in which forest conservation – particularly in the tropics – can help communities and society adapt to climate change, co-benefits associated with these adaptation strategies are innumerable. For example, non-timber forest products including food, fiber, and fuel are especially important for subsistence livelihoods. With regard to human health, tropical forest cover can moderate the spread of infection disease through regulating pathogen populations and their hosts (e.g., mosquitoes carrying malaria). Furthermore, biodiversity within these systems has yielded myriad medicinal natural products (Foley et al. 2007). Lastly, the climate change mitigation potential of forests is immense. The global forest carbon sink rate is estimated to be 2.4 Pg C/yr (Pan et al. 2011), though emissions from tropical deforestation and degradation effectively halve this rate. In terms of climate change adaptation strategies, there are no fathomable human-built alternatives to tropical forest conservation that deliver comparable co-benefits.

CONCLUSION

From agricultural lands to cities, from rivers and oceans to forests, the EbA approaches discussed above create a deep, diverse suite of co-benefits that technological adaptation measures do not. Whether the values of these co-benefits are high enough to make EbA strategies preferable to technological adaptations is an ongoing question. EbA approaches are usually more holistic and proactive in design than conventional interventions, which may be more reactive and focused on singular goals (e.g., levees for flood control; Jones et al. 2012). However, quantifying the future benefits of EbA can be challenging given the difficulty of accurately modeling ecosystems and a lack of consensus on how to place values on non-marketed ecosystem services for comparison purposes. These methodological difficulties can make engineered approaches more compelling because the costs and outcomes of such interventions are more easily quantified. Furthermore, the timeframe over which the primary benefits of EbA measures materialize may not always coincide with more immediate adaptation needs (Munroe et al. 2011). Thus, successful selection of adaptation measures requires identifying the contexts in which a given measure provides competitive adaptation options even if primary services aren't delivered for many years (Jones et al. 2012). Such accounting must also consider that EbA strategies – especially conservation and restoration ones – may be self-renewing and are inherently plastic whereas hard infrastructure and engineering solutions may end up mismatched to future conditions.

In the best of circumstances, EbA approaches coincide with and reinforce human health and poverty alleviation goals. For example, global health experts have hypothesized that climate change, deforestation, poverty, and civil unrest interacted to lay the stage for the 2014 West African Ebola outbreak (Bausch and Scwarz 2014). A prolonged dry season, linked to extreme deforestation and climate trends, may have driven the rural poor deeper into remaining forests in search of food and wood. As they expanded their geographic range and the variety of species they hunted, their risk of exposure to Ebola and other zoonotic pathogens increased. As exemplified in this case, poverty alleviation strategies and forest restoration for EbA may reinforce one another – though the danger remains that such EbA efforts may unintentionally undermine development efforts (e.g., conservation schemes that disenfranchise or exclude local peoples; Tallis et al. 2008).

Despite these potential shortcomings and trade-offs, positive synergies between EbA approaches, other climate change mitigation efforts, and conservation are highly likely. This is particularly true because EbA inherently seek to improve or augment the resilience of systems, thereby reducing the risks of crossing tipping points and shifting to unmanageable or unrecoverable states (Jones et al. 2012). Achieving such system resilience and harnessing nature to buffer communities from climate change impacts requires cross-scale coordination. Natural processes and ecosystem services do not conform to political boundaries, human institutions, or specific landscapes. Relying upon and safeguarding the ecosystem service of pollination, for example, requires individual and collective actions – perhaps mediated by top-down government incentives (Cong et al. 2014) – from agricultural landscapes to cities. Lastly, in undertaking any EbA effort, we must evaluate the potential for benefits to persist through time and across space (Munroe et al. 2011). After all, the very systems and processes we seek to leverage through EbA are also subject to unforeseen climate impacts.

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BOX 1: GLOSSARY

Agroecosystem: A holistic agricultural system that is typically small-scale and that leverages natural ecosystem processes (e.g., nutrient cycling, energy flows, and biotic interactions between diverse species) in management practices in a way that minimizes synthetic inputs.

Carbon sequestration: The removal and storage of carbon dioxide from the atmosphere and into carbon sinks (e.g., oceans, vegetation, geologic formations deep underground) through physical or biological processes.

Green Infrastructure: Any of a variety of stormwater-management techniques, installations or systems that use vegetation, soils, and natural processes as compared to engineered water collection systems of storm drains and pipes.

Hard adaptation approaches: Strategies for adapting to climate change that tend to use specific technologies, infrastructure, and actions that may require more capital goods and be more permanent than other adaptation approaches (e.g., sea walls to ward against sea-level rise).

Resilience: The capacity of a human or natural system to regain the essential components and processes that characterize the system after a perturbation or various stressors. Thresholds or tipping points are crossed when a system does not return to its characteristics state following a perturbation.

Resistance: The capacity of a human or natural system to maintain its essential components and processes despite a perturbation or various stressors.

Soft adaptation approaches: Strategies for helping communities adapt to climate change that primarily relate to social systems, knowledge transfer, and human behavior (e.g., livelihood diversification, establishment of early warning systems).

Soil organic carbon (SOC): The pool of carbon occurring in organic form in the soil, usually contained in soil organic matter (e.g., dead plant and animal tissue, decomposition byproducts, soil microbial biomass). It is the primary source of energy for soil microorganisms and serves as a good proxy for soil biodiversity.

Sea-level rise (SLR): The global and local rise in sea level due to a change in ocean volume. A volume change can result from an increase in the amount (i.e., mass) of water in the oceans (e.g., due to melting ice caps) and from the thermal expansion of ocean water as its temperature rises. Changes in salinity may also impact sea level.

Urban Greenspace: Lands in urban areas that are primarily covered by vegetation. Greenspaces can be publically or privately owned, and include a variety of maintenance and management regimes from golf courses and cemeteries to protected natural forests.

Urban Heat Island (UHI): The common phenomenon of warmer air and surface temperatures in urban areas compared to nearby rural areas. The pavement and dark building materials of urban areas have lower albedo -- they do not reflect as much solar energy. The temperature differential, typically 1-3 degrees C on an annual basis for a city of 1 million, can be as high as 12 degrees C at night.

FIGURE 1

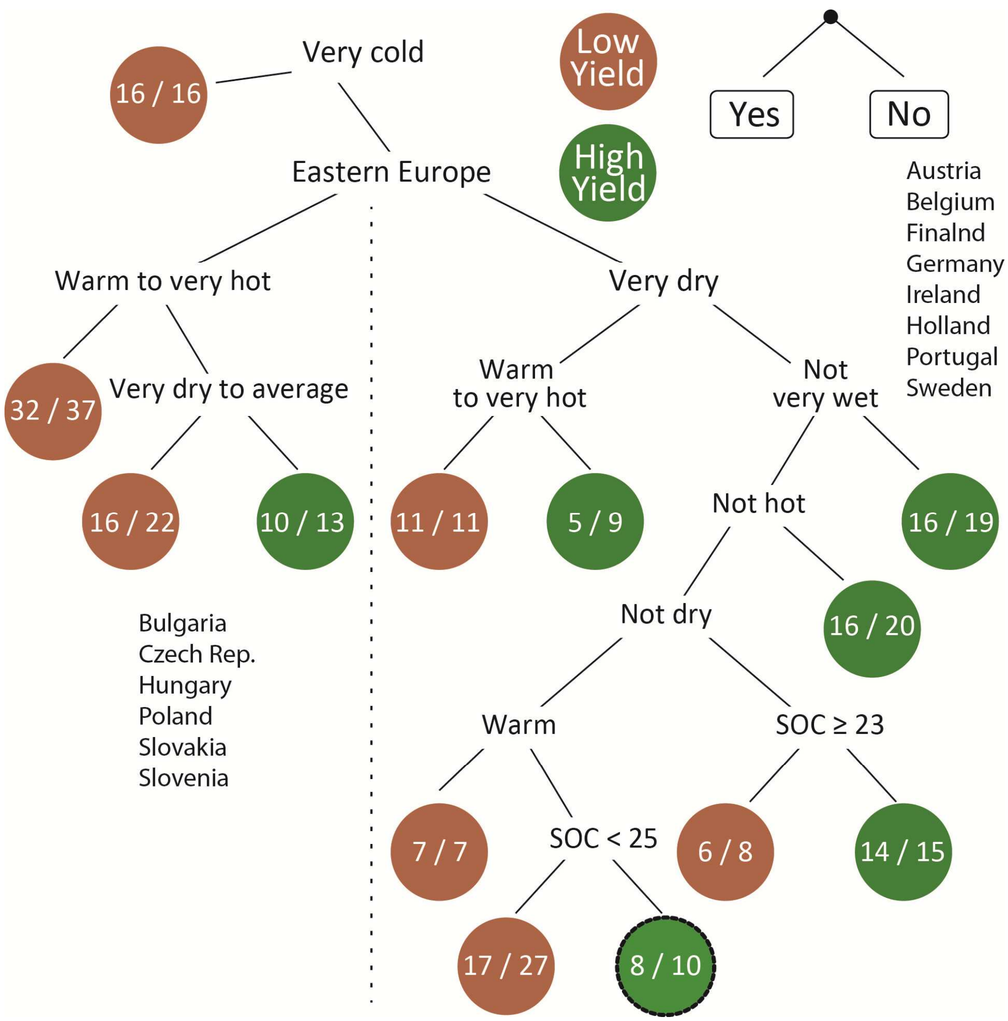


Figure 1. Classification tree for 2009 crop yields in Europe as explained by growing season weather and SOC. The tree represents the partitioning of 2009 crop-specific growing season weather and SOC across Europe that best explains a sample of observed 2009 yields. Observed yields are either placed in the lower yield bin (a bottom 50th percentile yield observation for the given crop) or the higher yield bin (a top 50th percentile yield observation for the given crop). At each node a "yes" to the weather or soil characteristic means a move to the left best fits the data and a "no" means a move to the right best fits the data (Loh 2011, Varian 2014). A "yes" on the Eastern Europe nodes indicates that the observation is from an Eastern Europe. Eastern European farms tend to use less chemical inputs and are less capitalized than their Western European counterparts.

At the end of each branch, called a leaf, the first number gives the count of observations on that branch that are in the given yield bin and the second number is the number of observations on that branch. For example, the higher yield '8/10' leaf (highlighted by dashed black border) indicates that eight Western Europe yield observations with higher yields did not experience very extreme growing season weather and had an SOC of 25 g kg^{-1} or more. In contrast, only two lower Western European yields had similar weather and soil conditions. In other words, observations on this branch are predicted to have a top half yield. The other SOC node, SOC $\geq$ 23, indicates that observations with that branch's growing season weather profile are much more likely to have a top half yield if SOC < 23 g kg^{-1}. In other words, in this leaf's particular growing season weather profile, too much SOC is associated with lower yields. All in all, SOC impacts yield at the margin while growing season weather and agricultural investment (crudely represented by Eastern versus Western European observations) are the main drivers of observed yields. See http://www.bowdoin.edu/faculty/e/enelson/ for more details on this analysis.

FIGURE 2

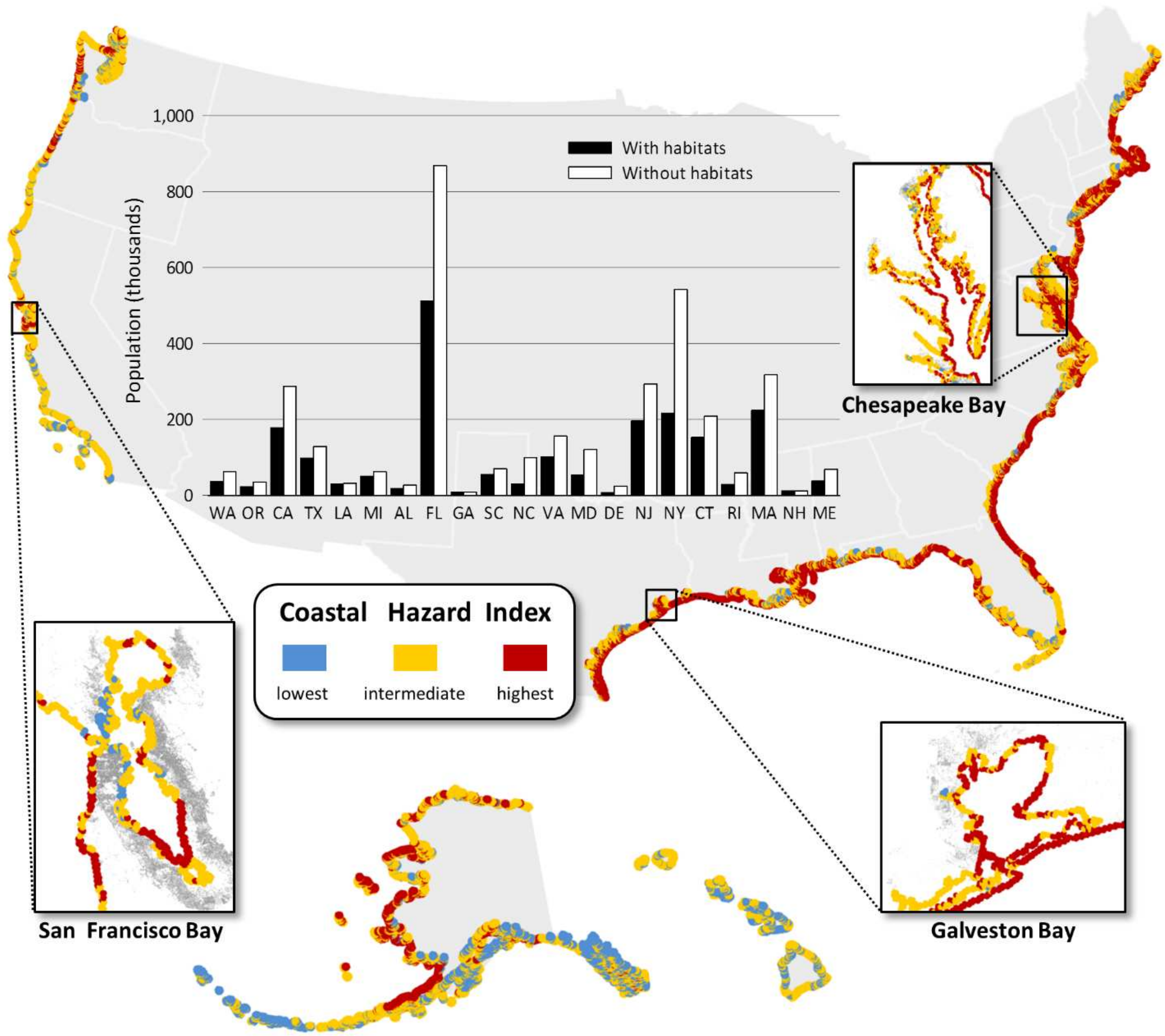


Figure 2. Exposure of the US coastline and coastal populations to sea-level rise in 2100 (A2 scenario; Parris et al. 2012) and storms. Warmer colors indicate regions with more exposure to coastal hazards (index >3.36). The bar graph shows the population living in areas most exposed to hazards (red 1km^2 coastal segments in the map) with protection provided by habitats (black bars) and the increase in population exposed to hazards if habitats were lost owing to climate change or human impacts (white bars). Letters on the x axis represent US state abbreviations. This figure first appeared in the journal Nature Climate Change (Arkema et al. 2013).

Supporting Information for Figure 1 in Chapter xx: Ecosystem-based adaptation in Climate Change and Biodiversity

A. Introduction

In Figure 1 of Chapter xx: Ecosystem-based adaptation in Climate Change and Biodiversity we use a classification tree (Loh 2011) to explain how growing season weather, soil organic carbon (SOC), and agriculture investment determined 2009 yields in Europe. We are particularly interested in the role that SOC plays in yield given that it is an imperfect substitute for nitrogen fertilizer. Preliminary analysis (e.g., Brady et al. 2015) has shown that as SOC increases in a field, the level of N application that optimizes yield decreases. Not only would this save the farmer money on fertilizer but it would reduce a host of negative externalities caused by N use.

In this analysis we do not include N fertilizer as an explanatory variable. Instead we use the location of a yield observation to control for fertilizer use and the overall level of investment in agriculture on the landscape. Data shows that farmers in countries that were part of the Warsaw Pact use less fertilizer and have lower levels of overall investment in agriculture than their western European counterparts. Thus we use an observation's host country to classify the observation as a low fertilizer and low investment observation (any observation from a former Warsaw Pact country) or as a high fertilizer and high investment observation (any other observation).

In the next iteration of this analysis we will use published N fertilizer rates as an explanatory variable.

In section B I describe the data used in the analysis. In section C I describe the how we analyzed the data.

B. Data

The dataset's spatial unit is the EU's smallest sub-country administrative unit, NUTS3 (Nomenclature of Territorial Units for Statistics; cite for GIS layer). For example, Skåne, a Swedish region, is a NUTS3 unit. We index NUTS3 regions with j.

Another major source of data in this study is the land survey LUCAS 2009 (cite). In this survey land across Europe in 2009 was sampled. We retained every 2009 sample that occurred on cropland. Each cropland sample indicates the crop grown on the land. We index crops with i. Some of these sample points also include information on irrigation practices and soil characteristics. All sample points in LUCAS 2009 are geo-located.

The other major data source used in this study is the NUTS2-level crop yield data from 2009 (NUTS2 is one administrative level up from NUTS3; a NUTS2 region is comprised of several NUTS3 regions). This data is from Eurostat (2014)[4]

1. Assigning 2009 crop-specific soil organic carbon and yields to each NUTS3 region

We tallied the number of LUCAS samples from maize fields, from wheat fields, etc taken from each NUTS3 unit j. We also tallied the number of each crop's samples in NUTS3 j that included soil

[4] http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/search_database

data. For each unique NUTS3 region-crop combination ji we averaged soil organic carbon (SOC; g / kg) over the samples with soil data. For example, suppose 10 maize fields were sampled from NUTS3 region j and 6 of these samples have soil data. We averaged SOC observations over the 6 maize samples with soil data to get $SOC_{j,maize}$. We found SOC_{ji} for all ji combinations. (When none of crop i's samples in region j had soil data then SOC_{ji} does not exist for that ji combination.)

We looked for crop yield data for every crop type included in the LUCAS 2009 sample. Let y_{ki} indicate 2009 yield of crop i in NUTS2 k where yield is measured in 100 kg / ha units. Let y_{kj} indicate 2009 yield of crop i in NUTS2 j. We chose not to simply set $y_{ji} = y_{ki}$ for all $j \in k$. Instead we set $y_{ji} = y_{ki}$ for the NUTS3 region j in k that had the most observations of crop i across all $j \in k$. All other NUTS3 regions j in k were assigned a yield of 0 for crop i ($y_{ji} = 0$). For example, suppose there are 3 NUTS3 regions, $j_k = 1, 2,$ and 3, in NUTS2 region k. Suppose the maize observations in these three NUTS3 regions number 6, 14, and 3, respectively. Suppose the 2009 maize yield in NUTS2 region k is 100. Then $y_{2,maize} = 100$ (NUTS3 region $j = 2$) and $y_{1,maize} = y_{3,maize} = 0$ (NUTS3 regions $j = 1, 3$).

We believe this conservative NUTS3 yield assignment algorithm is the best way to avoid yield misspecification errors when downscaling yields from the NUTS2 region to the NUTS3 region. For example, consider our simple example immediately above. Assuming the LUCAS sample is representative of the actual distribution of maize fields across the NUTS2 region, NUTS3 region $j = 2$ had the majority of NUTS2 k's 2009 maize fields. Therefore, we can assume with a high degree of confidence that the average maize yield in $j_k = 2$ was approximately 100 in 2009. Suppose not, suppose the average yield in $j_k = 2$ was, for example, 50. To have an average yield of 100 in NUTS2 k the average yield in $j_k = 1$ and 3 would have to be very high. For example, the weighted average,

$$(6/23) \times 178 + (14/23) \times 50 + (3/23) \times 178 = 100$$

would generate an average NUTS2 yield of 100. But maize yields of 178 100 kg ha^{-1} are impossible. Conversely, the weighted average,

$$(6/23) \times 76 + (14/23) \times 115 + (3/23) \times 76 = 100$$

also generates a NUTS2 average yield of 100 but with more realistic yield possibilities. And notice assigning a yield of100 to $j_k = 2$ generates less error (115 – 100 / 100 = 0.15) than assigning a 100 yield to $j_k = 1$ and 3 (76 – 100 / 100 = 0.24).

If two or more NUTS3 regions in a NUTS2 region had the highest number of observations of crop i we set $y_{ji} = y_{ki}$ for all NUTS3 region j in k that shared the high count.

2. Calculation of 2009 crop-specific growing degree days and precipitation in each NUTS3 region

First, we determined the planting and harvest days for each crop in each NUTS3 region with 0.5 degree maps of planting and harvest dates from the Crop Calendar Dataset. [5] For each crop there are maps that give the earliest date, the average date, and latest date for planting and harvest. We used the average date. Crops with maps include Barley (Winter), Barley (Spring), Maize (main

[5] http://www.sage.wisc.edu/download/sacks/crop_calendar.html. We used the filled (extrapolated) datasets.

season), Oats (Spring), Potatoes, Pulses, Rapeseed (Winter), Rice (main season), Rye (Winter), Soybeans, Sugarbeets, Sunflower, Wheat (Winter), and Wheat (Spring).

Second, we download daily minimum and maximum temperatures (in Kelvin) for every day of 2008 and 2009 at 0.5 degree the NCEP database for the area bounded by the following decimal degrees Min X: -24; X Max: 45; Min Y: 34; and Max Y: 71. This area is a rectangle that covers all of Europe. Third, we download monthly precipitation levels (in mm) from the CRU_TS3.20 database for every month of 2008 and 2009 at 0.5 degree for the same rectangular area. We obtained this data from the website DataGuru.[6]

Third, we wrote a MATLAB script that uses the planting and harvest day data to determine which days in 2008 and 2009 each crop type i would have been growing at each 0.5 degree point in Europe (we have to include some days in 2008 for winter crops; all harvests take place in 2009, however). Some points in Europe had no plant and harvest data for one or more crops. We assumed the growing season for these crops at these points was 0 days.

Next, we wrote a MATLAB script then sends the daily temperature data at each point in space along with the growing season start and end days at that point to a Growing Degree Day (GDD) function that determines the GDD for each crop at each point in Europe for 2008-2009. We use two methods to determine GDD, and thus we have two GDD measures for each crop at each spot (McMaster and Wilhelm 1997). If a crop has a growing season of 0 at some point then the GDD measures for that crop at that spot are 0. Let GDD_{zim} indicate the 2008-2009 GDD at point z $\{j = 1,\ldots,10212\}$ for crop i $\{i = 1,\ldots,14\}$ under calculation method m $\{m = 1,2\}$.

Next, we wrote a MATLAB script that takes the monthly precipitation levels at each point in Europe and converts them into daily levels for that month by simply dividing monthly levels by the number of days in that month. In other words, each day is assigned its month's average daily precipitation.

Next, we wrote a MATLAB script then sends the (average) daily precipitation data at each point in space along with the growing season start and end days at that point to a function that determines the growing season precipitation (in mm) for each crop at each point in Europe for 2008-2009 (this is simply a sum of all daily precipitation during the growing season). If a crop has a growing season of 0 at some point then the precipitation measure for that crop at that spot is 0. Let PRE_{zi} indicate the 2008-2009 precipitation at point z $\{z = 1,\ldots,10212\}$ for crop i $\{i = 1,\ldots,14\}$.

Finally, we wrote a MATLAB script that finds the mean GDD_{zim} and mean PRE_{zi} for each crop i in each NUTS3 region j $\{j = 1,\ldots,1454\}$. Let these values be given by GDD_{jim} and mean PRE_{ji}. If region j has no GDD_{jim} and PRE_{ji} values then the region's GDD_{jim} and mean PRE_{ji} are set equal to its nearest neighbor's GDD_{jim} and PRE_{ji} values, respectively.

3. Creating the variables used in our yield model

Each ji combination with $y_{ji} > 0$, $SOC_{ji} > 0$, $GDD_{jim} > 0$, and $PRE_{ji} > 0$ is retained in our dataset. This pared dataset has 280 observations. For each crop i the following were calculated,

[6] http://dataguru.nateko.lu.se/

$$\overline{GDD}_{im} = \frac{1}{\sum_{j=1}^{J} I(GDD_{jim}>0)} \sum_{j=1}^{J} GDD_{jim}$$

$$\overline{PRE}_{i} = \frac{1}{\sum_{j=1}^{J} I(PRE_{ji}>0)} \sum_{j=1}^{J} PRE_{ji}$$

where $I(GDD_{jim} > 0) = 1$ and $I(PRE_{ji} > 0) = 1$ means that $\sum_{j=1}^{J} I(GDD_{jim} > 0)$ and $\sum_{j=1}^{J} I(PRE_{ji} > 0)$ equals the number of NUT3-level crop i observations retained in our dataset. Therefore, $\overline{GDD}_{im}$ and $\overline{PRE}_{i}$ are *i*'s average 2009 GDD and growing season precipitation over the NUTS3 regions that are associated with crop *i*. Then for each combination of *ji* retained we calculated

$$NGDD_{jim} = 100\left(\frac{GDD_{jim}-\overline{GDD}_{im}}{\overline{GDD}_{im}}\right)$$

$$NPRE_{ji} = 100\left(\frac{PRE_{ji}-\overline{PRE}_{i}}{\overline{PRE}_{i}}\right)$$

In other words, $NGDD_{jim}$ and $NPRE_{ji}$ indicate *j*'s crop-specific deviation from the crop's European-wide average 2009 GDD and growing season precipitation. Therefore, observations with positive (negative) *NGDD* had GDD measures greater (lower) than the average for their crop group where *NGDD* values further and further away from 0 meant more extreme weather relative to the crop's average growing season. The same interpretations apply for *NPRE*.

Finally we create a yield bin variable for each *ji* where $yb_{ji} = 1$ if y_{ji} is in the 0 to 25th percentile of the $\{y_{1i}, \ldots, y_{Ji}\}$ distribution, $yb_{ji} = 2$ if y_{ji} is in the 25th to 50th percentile of the $\{y_{1i}, \ldots, y_{Ji}\}$ distribution, $yb_{ji} = 3$ if y_{ji} is in the 50th to 75th percentile of the $\{y_{1i}, \ldots, y_{Ji}\}$ distribution, and $yb_{ji} = 4$ if y_{ji} is in the 75th to 100th percentile of the $\{y_{1i}, \ldots, y_{Ji}\}$ distribution.

We also create an alternative definition of $yb_{ji} = 1$ if y_{ji} is in the 0 to 50th percentile of the $\{y_{1i}, \ldots, y_{Ji}\}$ distribution and $yb_{ji} = 2$ if y_{ji} is in the 50th to 100th percentile of the $\{y_{1i}, \ldots, y_{Ji}\}$ distribution. Therefore, observations with higher bins had greater than average yields in their crop group.

C. Classification tree modeling

Next we predict (or explain) *yb* as a function of OC, NGDD, NPRE, and the variable East where East equal 1 if the observation comes from a country that was part of the Warsaw Pact (typically Eastern Europe).

In data analysis we are often interested in finding a function that provides a good prediction of y as a function of $\mathbf{x} = (x_1,\ldots,x_p)$. Suppose our goal is to find a predictive function where *y* is a categorical variable like yield bin (*yb* can take on the integer values of 1 to 4 or 1 to 2, depending on the number of bin categories). We could use discrete variable regression to predict or "fit" the effect that **x** has on y. Regression analysis is the technique that economists most often use to find such prediction functions. We can also using machine learning techniques to find predictive functions. Analyzing categorical dependent variable datasets with machine learning is known as the classification problem.

A decision tree is a machine learning classifier. In a tree, each observation ends at a tree leaf based on its **x** values. In our case a tree leaf will be a yield bin. The goal of machine learning is to construct a decision tree that leads to good out-of-sample predictions. In other words, a well-constructed tree not only directs most observations used to construct the tree to their observed outcome but would also do so with data not used to construct the tree. Trees tend to fit (y | **x**) better than discrete variable regression when nonlinearities in $x_1,\ldots,x_P$ and interactions between $x_1,\ldots,x_P$ are important in explaining y. Evidence suggest that crop yield is largely explained by weather and soil nonlinearities and interactions.

To find a well-constructed tree we use R package **rpart** to do the following,

1. We randomly divide the dataset of 280 observations into two folds of approximately 210 observations (the training dataset) and 70 observations the (testing dataset).
2. We use the training dataset to grow a tree that predicts yield bin (*yb*) with SOC, NGDD, NPRE, and East for a particular complexity parameter (CP).
3. We then predict tree leaf distribution with the excluded fold and calculate the out-of-sample classification error.
4. We repeat steps 1 – 3 1000 times.
5. We retain the mean and variance of the sample classification error.
6. We repeat steps 1 -5 we CPs of (0.005, 0.010, 0.015, …, 0.045)
7. We retain the CP that minimizes out-of-sample classification error.

The CP indicates how aggressively to "prune" the tree by recursively snipping off the least important splits. The higher the complexity parameter, the more aggressive the pruning. In the table below we report the mean and variance of out-of-sample classification error for CPs of (0.005, 0.010, 0.015, …, 0.045) when *yb* is comprised of two bins or four bins.

Table 1: Model Accuracy

	Two bins		**Four bins**	
CP	**Mean**	**Variance**	**Mean**	**Variance**
0.002	0.360	0.0032	0.517	0.0031
0.005	0.359	0.0034	0.519	0.0031
0.010	0.358*	0.0032	0.519	0.0030
0.015	0.359	0.0031	0.514*	0.0027
0.020	0.361	0.0032	0.508	0.0029
0.025	0.360	0.0030	0.502	0.0032
0.030	0.359	0.0030	0.507	0.0032
0.035	0.364	0.0031	0.508	0.0032
0.040	0.367	0.0031	0.512	0.0037
0.045	0.376	0.0035	0.513	0.0035

D. Classification tree modeling results

Next we ran the training dataset and the two yield bin dependent variable through **rpart** eight times using a CP of 0.010. I used the CP of 0.010 because it minimizes out-of-sample classification error with two yield binds. After each run I saved the estimated tree's graphical representation. The eight trees using the two yield bin dependent variable are presented in Figure S1.

Figure S1: A

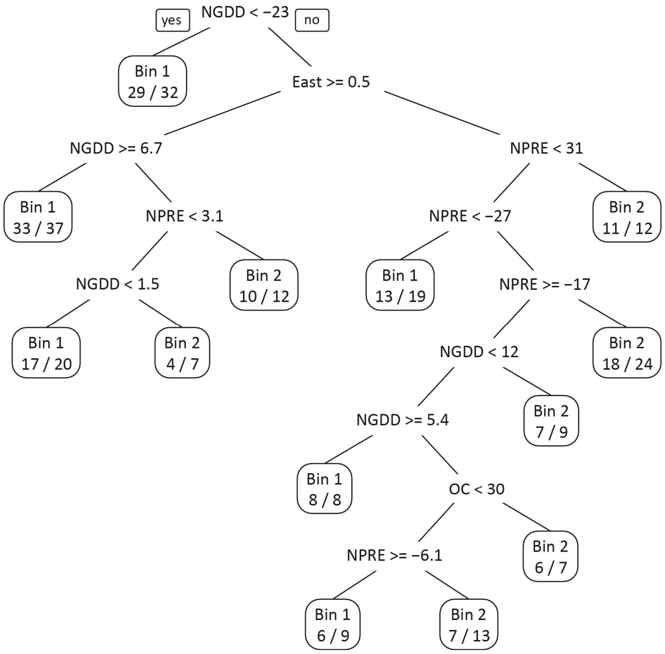


Figure S1: B (version in book chapter)

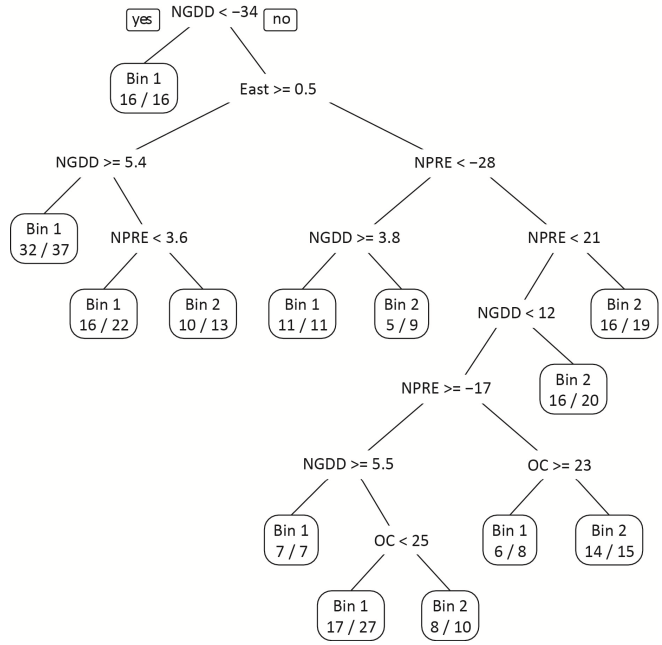


Figure S1: C

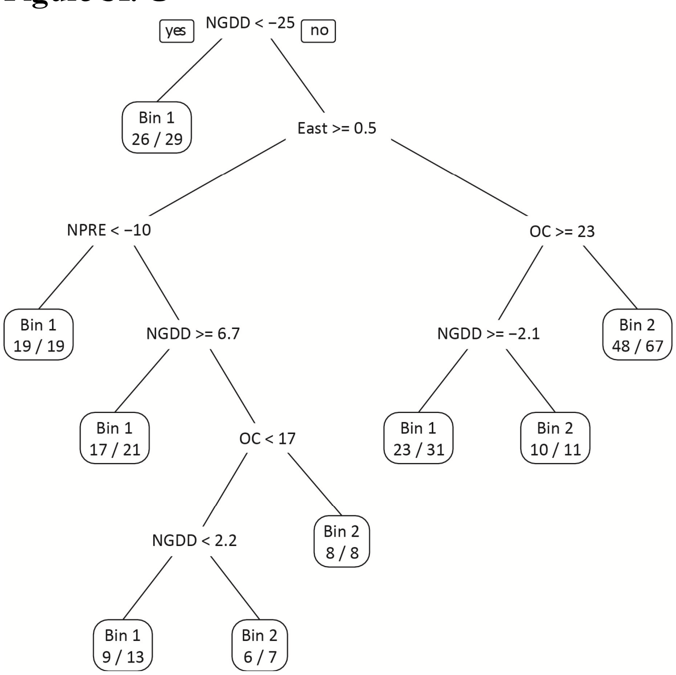


Figure S1: D

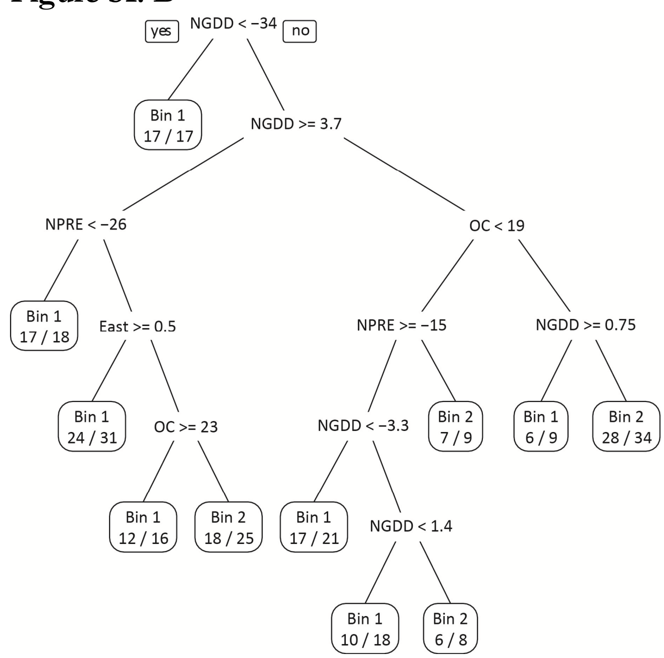


Figure S1: E

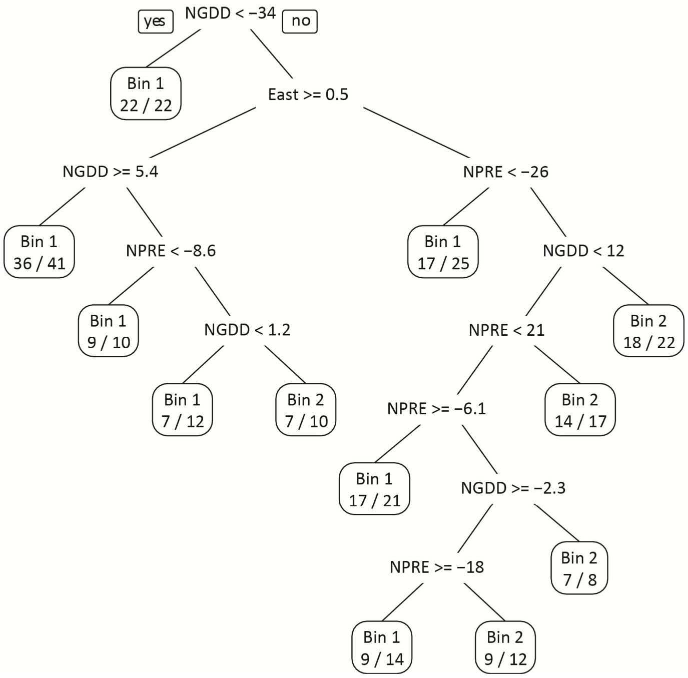


Figure S1: F

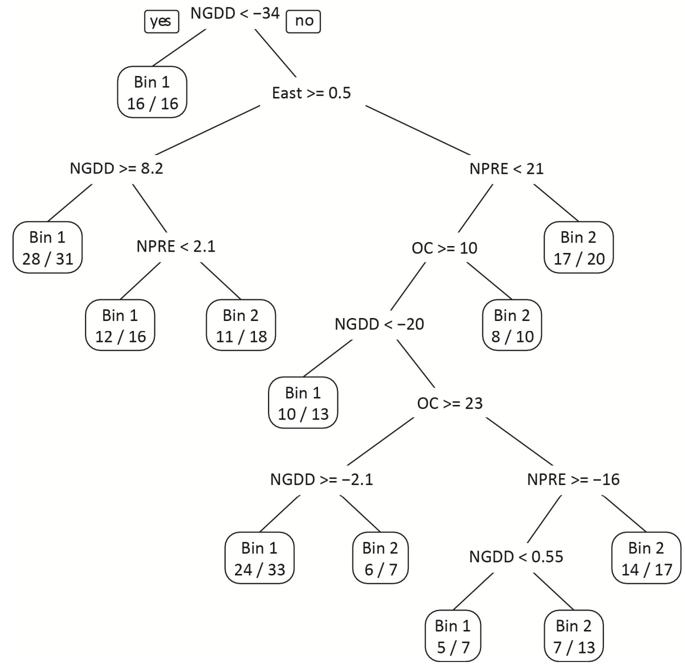


Figure S1: G

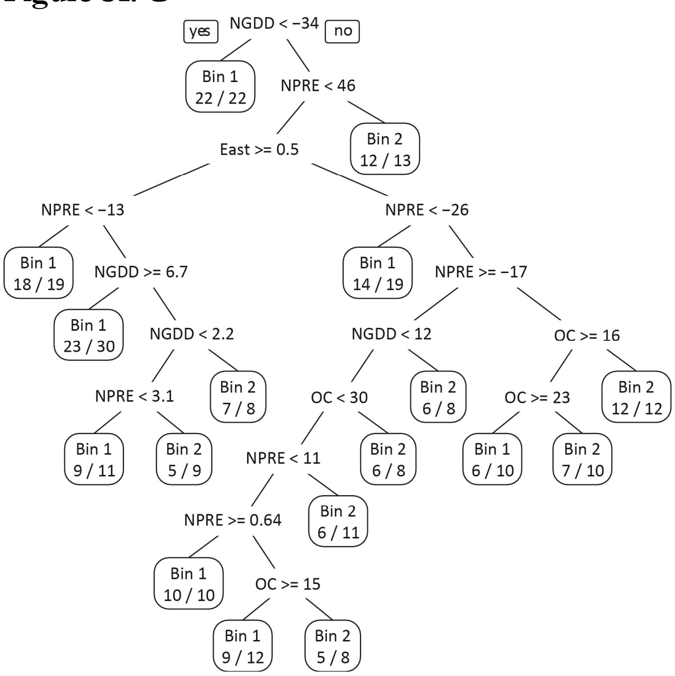
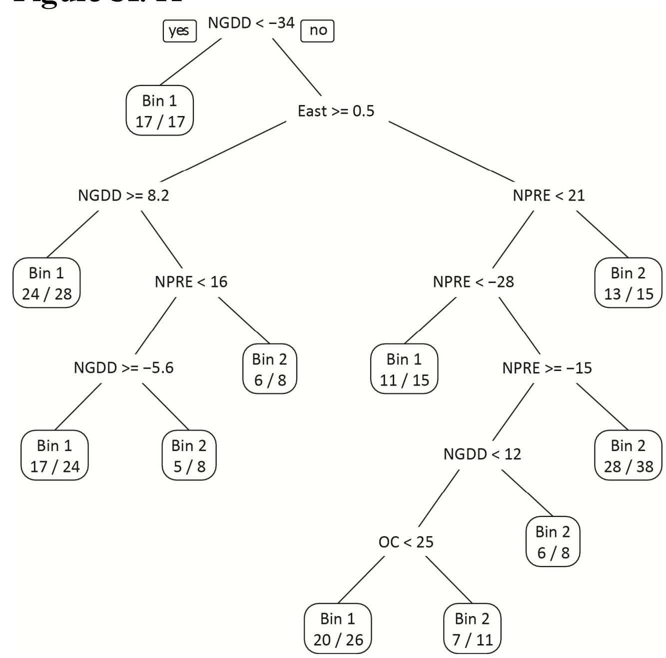


Figure S1: H



At each node a "yes" to the inequality means a move to the left best fits the data and a "no" means a move to the right best fits the data (Loh 2011, Varian 2014). At each leaf (the end of an entire branch) the first number is the observations on the leaf that are in the given yield bin and the second number is the total number of observations on that leaf.

In all cases, growing season weather is the first node. Extremely low (NGDD ≤ -27 or NGDD ≤ -34) GDD measures are predicted to results in bin 1 yields. Next the data is partitioned by the variable "East" 7 out of 8 times. When "East" is the second node former Warsaw Pact observations are only expected to reach yield bin 2 if growing season temperature and precipitation is slightly higher than normal. In one case SOC values of 17 or more are associated with yield bin 2 in former Warsaw Pact observation. However, in general, SOC has little impact in eastern European yields.

In Western Europe, SOC has yield impact on the margin. A growing season precipitation node occurred before an SOC node 6 out of 8 times in Western Europe. In most cases very high SOC measures were associated with bin 2 yields. In several cases higher SOC values seemed to prevent bin 1 yields when the growing season weather was less than ideal. For example, consider panel D. Observations with NGDD between – 34 and 0.75 were associated with a bin 2 yield as long as OC was greater than 19. Otherwise, NGDD had to be greater than 1.4 for an observation to fit into the second yield bin.

I ran the training dataset with the four yield bin dependent variable through **rpart** eight times using a CP of 0.015. A CP of 0.025 minimizes out-of-sample classification error with the four yield bin dependent variable. However, this CP always prunes SOC. A CP of 0.015 is the largest CP that routinely retains the SOC variable. After each run I saved the estimated tree's graphical representation. Theses eight trees are presented in Figure S2.

Figure S2: A

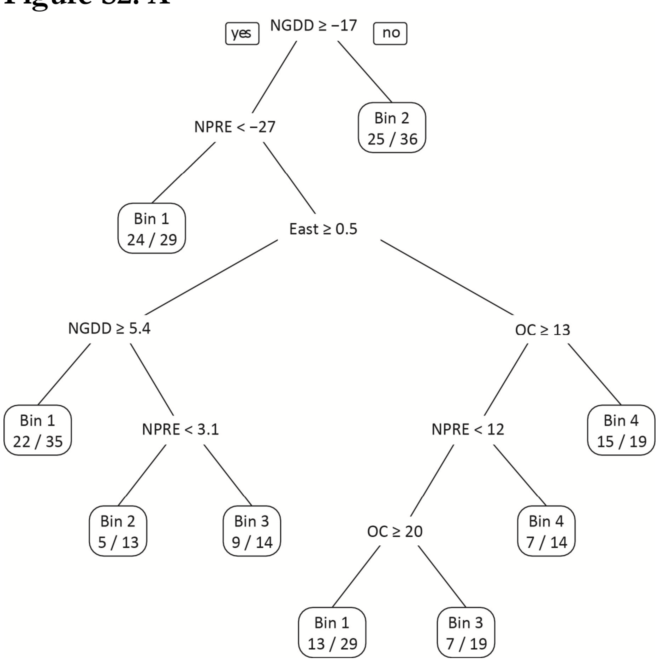


Figure S2: B

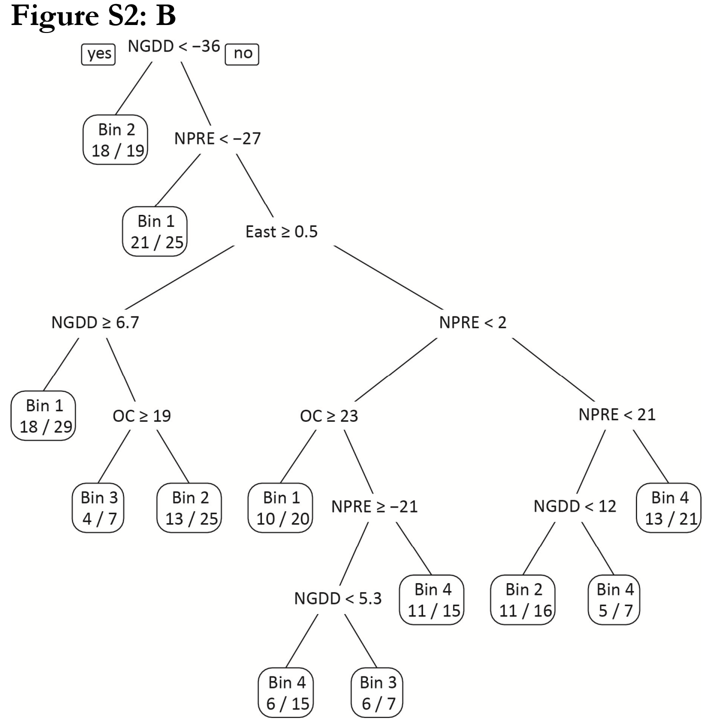


Figure S2: C

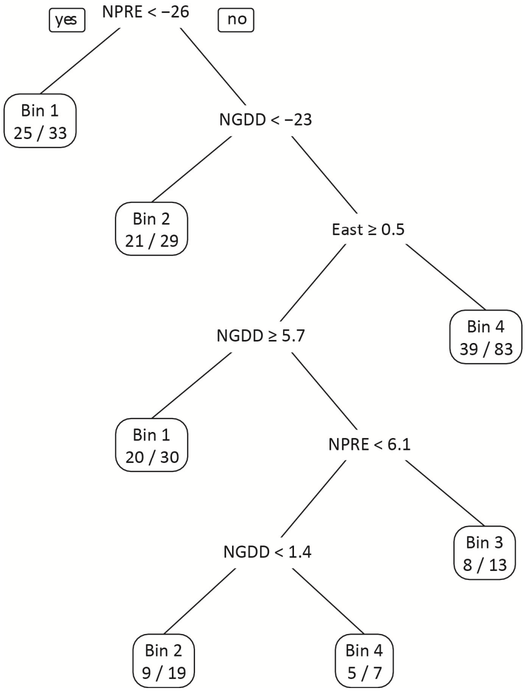


Figure S2: D

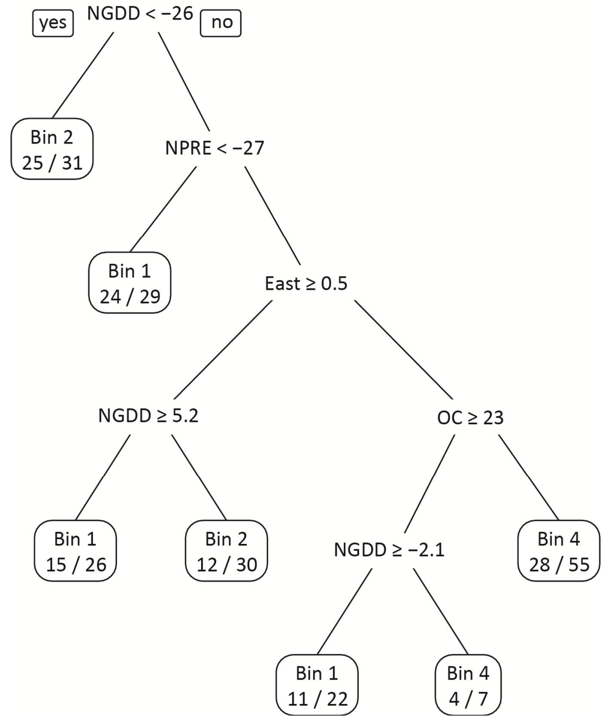


Figure S2: E

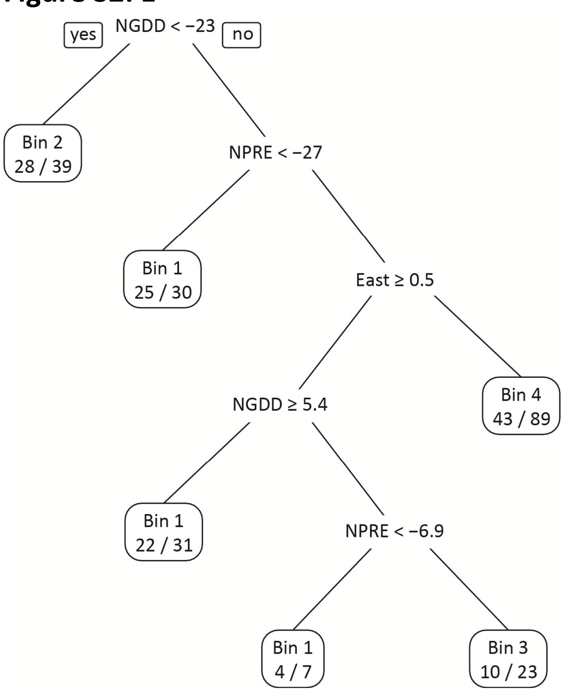


Figure S2: F

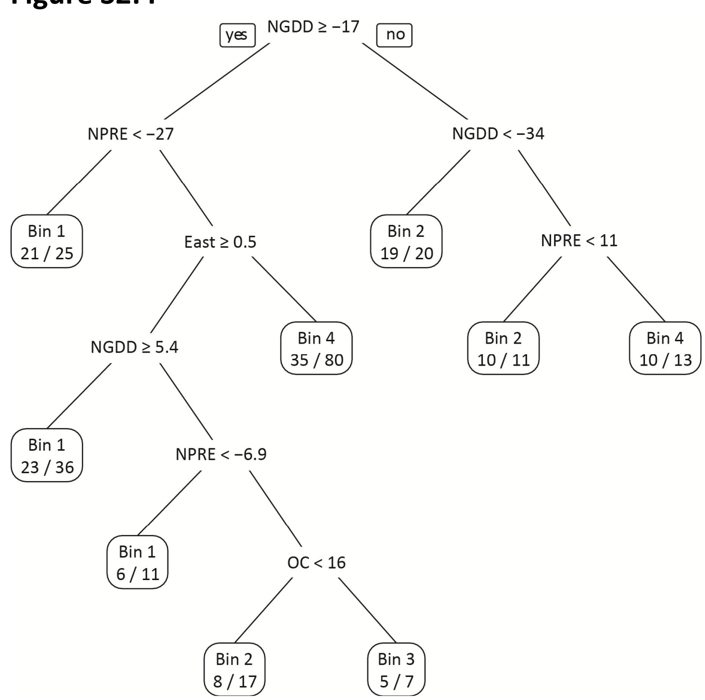


Figure S2: G

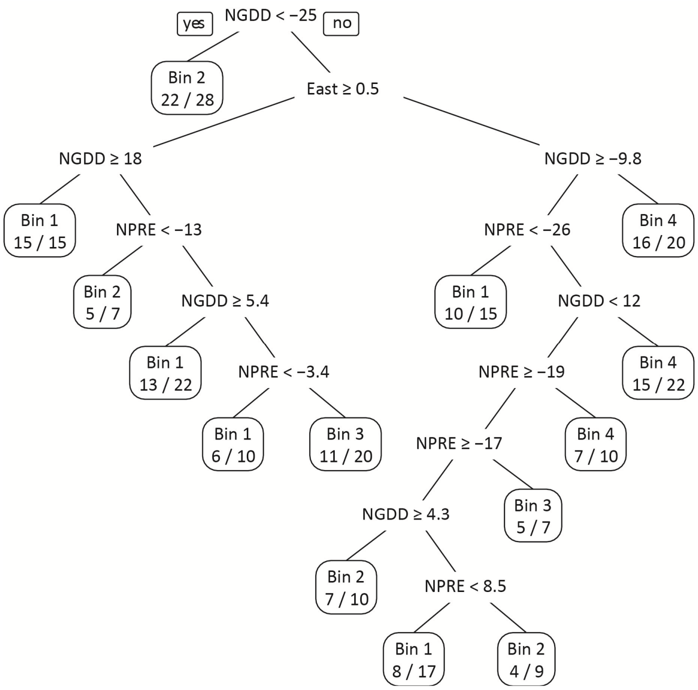
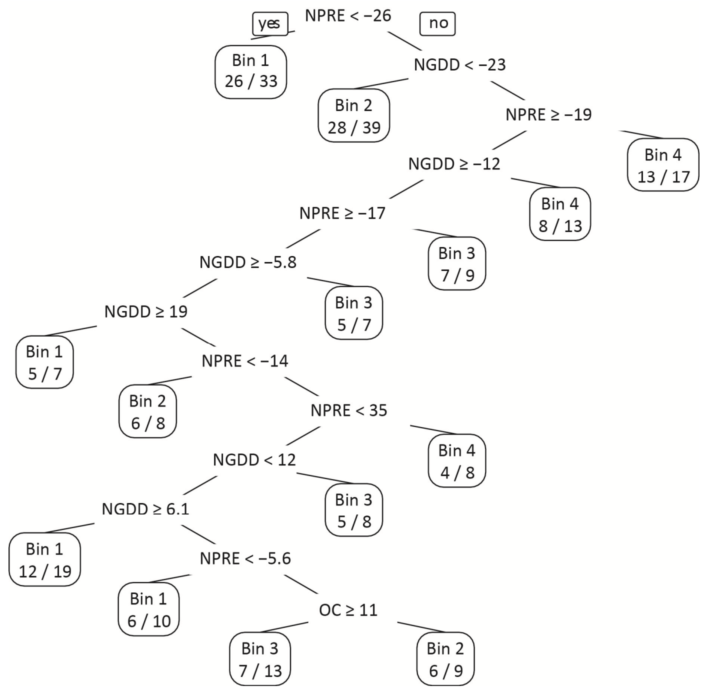


Figure S2: H



With the four yield bin dependent variable extremely low NGDD and NPRE values are the first two node of the tree. The variable “East” is typically the next variable to show up in the tree. As before SOC has little impact on Eastern European yields. And when SOC does impacts yield it only does so within very narrow growing season weather ranges. For example, consider Figure S2: H. SOC only has an impact with observations with a NGDD range of -5.8 to 6.1 and a NPRE range of -5.6 and 35. In that case OC levels of 11 or above marginally improve yield outcome. In Figure S2: F SOC only has an impact on Eastern observations with a NGDD range of -17 to 5.4 and a NPRE greater than 6.9. In that case OC levels of 16 or above marginally improve yield outcome. In Figure S2: A OC levels between 13 and 20 in Western EU observations were associated with yield bins 3 and 4 as long as NGDD was greater than -17 and NPRE was greater than -27.

We also used the r package **randomForest** to confirm the order of variable importance when predicting yield category. As exemplified by the decision trees, NGDD is the most important variable in explain yield bin, with NPRE, East, and OC following in order of importance (see Figures S3 and S4).

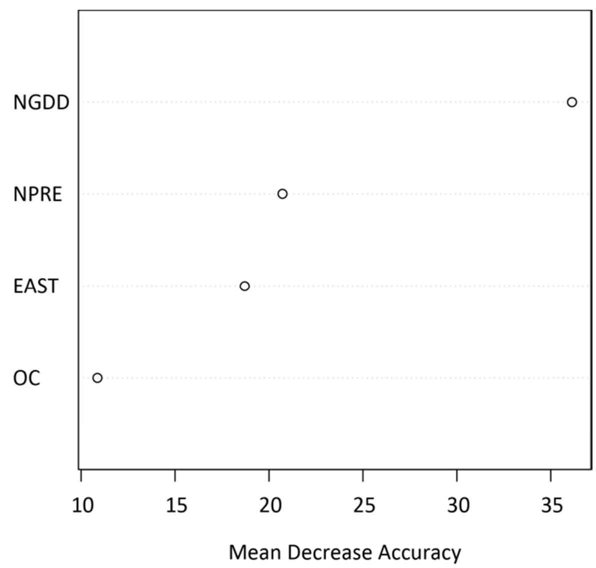


Figure S3: Random forest analysis of 2 yield bin model.

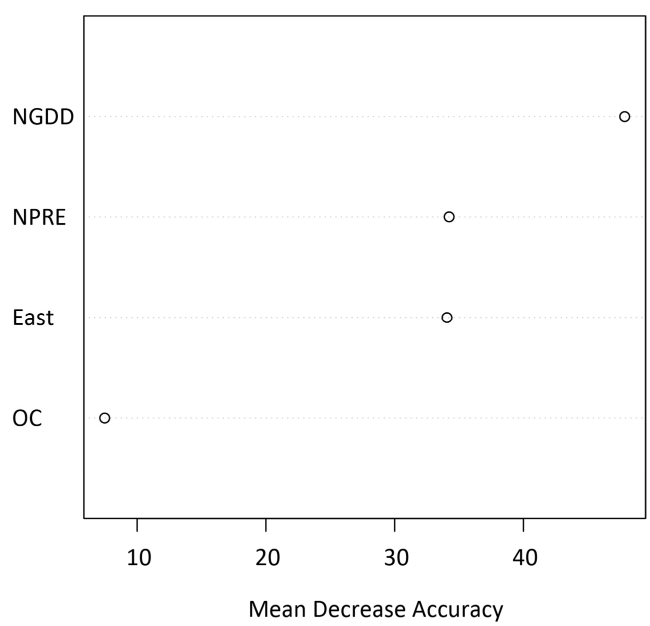


Figure S4: Random forest analysis of 4 yield bin model.