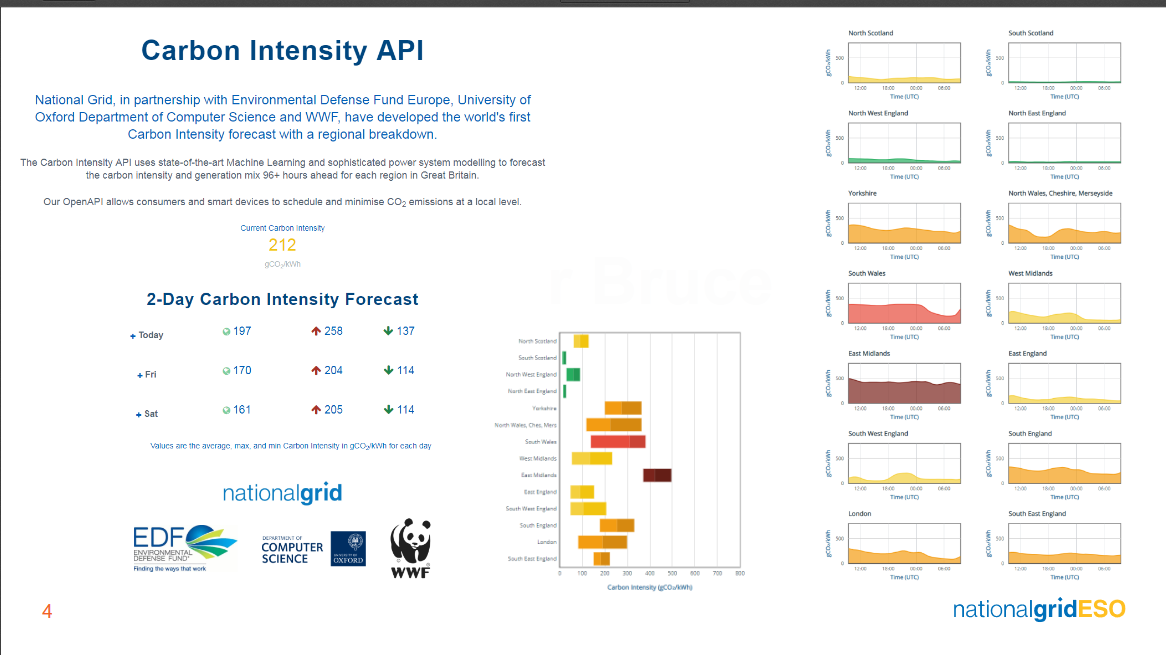
Climate change

1. Electrical Systems
2. Transportation
3. Buildings and cities
4. Industry
5. Climate Predicition

Electricity Systems by Priya L. DontiAI has been called the new electricity, due to its potential to transform entire industries.5Interestingly,electricity itself is one of the industries that AI is poised to transform. Many electricity systems are awash in data, and the industry has begun to envision next-generation systems (smart grids) driven by AI and ML.Electricity systems are currently responsible for about a quarter of human-caused greenhouse gas emis-sions. Moreover, as buildings, transportation, and other sectors seek to reduce their emissions impacts by replacing traditional fuels , demand for low-carbon electricity will grow even further. To reduce the impact of electricity systems across the globe, society must•Rapidly transition to low-carbon electricity sources (such as solar, wind, hydro, and nuclear) and phase out carbon-emitting sources (such as coal, natural gas, and other fossil fuels).•Reduce emissions from existing carbon-emitting power plants, since the transition to low-carbon fuels will not happen overnight.•Implement these changes across all countries and contexts,as electricity systems are everywhere.ML can contribute on all fronts by informing the research, deployment, and operation of electricity sys-tem technologies. Such contributions include accelerating the development of clean energy technologies,improving forecasts of demand and clean energy, improving system optimization and management, and en-hancing system monitoring. These solutions require a variety of ML paradigms and techniques, and warrant working closely with domain experts to integrate insights from operations research, electrical engineering,physics, chemistry, the social sciences, and other fields. Enabling low-carbon electricityLow-carbon electricity sources are essential to fighting climate change. These sources come in two forms: vari-able and controllable. Variable sources fluctuate based on external factors: for instance, solar panels produce power only when the sun is shining, and wind turbines only when the wind is blowing. On the other hand,controllable sources such as nuclear or geothermal plants can be turned on and off. These two types of sources have different implications for how electricity systems are run, and thus present distinct opportunities for ML techniques.

Variable sources



Most electricity is delivered to consumers using a physical network called the electric grid, where the power generated must equal the power consumed at every moment. This implies that for every solar panel, wind turbine, or other variable electricity generator, there is some mix of natural gas plants, storage, or other controllable sources ready to buffer unexpected changes in its output (which occur, for example, when there are unexpected clouds blocking the sun or the wind blows less strongly than was forecast). Today, this buffer is often provided by natural gas plants run in a standby mode that causes them to release CO2 even when not producing any power.In (future) low-carbon systems with a high reliance on variable resources, much of this buffer may need to be provided by energy storage technologies such as batteries , pumped hydro,or power-to-gas. However, managing such highly variable systems is complex,and system operators may be unable to transition towards this low-carbon future without improvements in key technologies.ML can both reduce emissions from today’s standby generators and enable the transition to carbon-freesystems by helping improve necessary technologies (namelyforecasting, scheduling, and control) and byhelping create advanced electricity markets that accommodate both variable electricity and flexible demand.Generation and demand forecasting High LeverageSince variable generation and electricity demand both fluctuate, they must be forecast ahead of time toinform real-time electricity scheduling and longer-term system planning. Better short-term forecasts can improve electricity scheduling, enabling operators to both reduce their reliance on polluting standby plantsand proactively manage increasing amounts of variable sources. Better long-term forecasts can improvesystem planning, helping operators understand where and how many variable plants should be built. Whilemany system operators today use basic forecasting techniques, forecasts will need to become increasinglyaccurate, span multiple horizons in time and space, and better quantify uncertainty to support these usecases.To date, many ML and deep learning methods have been applied to power generation and demandforecasting. These methods have employed historical data,physical model outputs, images, and even videodata to create short- to medium-term forecasts of solar power [32–40], wind power [41–45], hydro power[20], demand [46–49], or more than one of these [50, 51] at aggregate spatial scales. These methods spanvarious types of supervised machine learning, fuzzy logic,and hybrid physical models, and take differentapproaches to quantifying (or not quantifying) uncertainty. At a more spatially granular level, some demand forecasting work has attempted to understand specific categories of demand, for instance by using clusteringtechniques on households [52, 53] or using game theory, optimization, regression, and/or online learning topredict disaggregated quantities from aggregate electricity signals [54–56].While much of this previous work has used domain-agnostic techniques, ML algorithms of the futurewill need to meaningfully incorporate domain-specific insights. For instance, since weather fundamentallydrives both variable generation and electricity demand, MLalgorithms forecasting these quantities shoulddraw from innovations in climate modeling and weather forecasting (§7) and in hybrid physics-plus-MLmodeling techniques [33–35]. Such techniques can help improve short- to medium-term forecasts, and arealso necessary for ML to contribute to longer-term (e.g. year-scale) forecasts since weather distributionsshift over time [57]. In addition to incorporating system physics, ML models should also directly optimizefor system goals [58–60]. For instance, the authors of [58] use a deep neural network to produce demandforecasts that optimize for electricity scheduling costs rather than forecast accuracy (assuming schedulingis automated); this notion could be extended to produce forecasts that minimize GHG emissions. In non-automated settings where power system control engineers (partially) determine how much power each gen-9This standby mode is calledspinning reserve.10It is worth noting that in systems with many fossil fuel plants, storage can actually increase emissions depending on howit isoperated [29, 30].6

erator should produce, explainable ML and automated visualization techniques could help engineers betterunderstand forecasts and thus improve how they schedule low-carbon generators. More broadly, under-standing the domain value of improved forecasts is an interesting challenge for ML. For example, previouswork has characterized the benefits of specific solar forecast improvements in a region of the United States[61]; further study in different contexts and for differenttypes of improvements could help better direct theattention of the ML community within the forecasting space.Improving scheduling and flexible demandWhen balancing electricity systems, system operators use aprocess calledscheduling and dispatchto de-termine how much power each generator should produce.11This process is slow and complex, as it isgoverned by NP-hard optimization problems12that need to be coordinated across multiple time scales (fromsub-second to days ahead). However, scheduling becomes even more complex in a system with variablegenerators, storage, andflexible demand, since operators will need to manage even more system compo-nents while simultaneously solving scheduling problems more quickly to account for real-time variations inelectricity production. Scheduling processes must therefore improve significantly for operators to managesystems with a high reliance on variable sources.ML can help improve the existing (centralized) process of scheduling and dispatch by speeding up powersystem optimization problems. A great deal of work primarily in optimization, but also using techniquessuch as neural networks, genetic algorithms, and fuzzy logic [62], has focused on improving the tractabilityof power system optimization problems. ML could also be usedto fit fast function approximators to existingoptimization problems or to find good starting points for optimization. Dynamic scheduling [63, 64] and safereinforcement learning could also be used to balance the electric grid in real time to accommodate variablegeneration or demand; in fact, some electricity system operators have started to pilot similar methods atsmall, test case-based scales.While many modern electricity systems are centrally coordinated, recent work has examined how to(at least partially)decentralizescheduling and dispatch, primarily through advanced electricity markets.13In particular, storage and flexible demand can balance the electricity system by responding to real-timeprices that reflect (for example) how much variable electricity is available. ML or potentially even sim-pler techniques can enable flexible demand by helping storage and smart devices14automatically respondto electricity prices; previous work has optimized storageand/or flexible demand using techniques such asagent-based models [68–71], online optimization [72], anddynamic programming [73]. To provide appro-priate signals for flexible demand, system operators can design electricity prices based on e.g. forecasts ofvariable electricity (see the discussion above) or grid emissions (see§1.2). Previous work has used dynamicprogramming to set real-time electricity prices that maximize revenue [74], and similar techniques could beapplied to create prices that instead optimize for GHG emissions. In general, much more work is neededto test and scale existing decentralized solutions; barring deployment on real systems, platforms such as11Thisscheduling and dispatchprocess is used in bothregulatedelectricity networks (where a central entity more-or-lesscom-pletely determines which power plants will produce power) andderegulatedelectricity networks (where power plants bid to deter-mine who will produce power, but oversight for balancing theelectricity system ultimately falls upon a system operator).12For instance,unit commitmentis a (large) mixed integer program that includes nonlinear power flow constraints. Systemoperators often use simpler variants of this problem, but even these are often computationally complex.13For instance, researchers and entrepreneurs have proposeddistributed energy trading or management systems that enablevariable low-carbon energy. Some of these suggested distributed systems include transactive energy systems [65, 66] and peer-to-peer energy trading systems [67]. Some companies also propose to run truly distributed markets within existing electricity marketstructures (see e.g. Camus Energy:https://camus.energy/).14Some modern electricity operators are already beginning toprocure autonomous flexible demand for grid-balancing purposes.For instance, the Southern California Edison electricity supply company has procured 50 MW ofdemand responsefrom Nest smartthermostats to prevent electricity blackouts. Seehttps://www.greentechmedia.com/articles/read/inside-nests-50000-home-virtual-power-plant-for-southern-california-edison.7

PowerTAC15can provide large-scale simulated electricity markets on which to perform these tests.Accelerated science for materialsHigh LeverageHigh RiskLong-termScientists are working to develop new materials that can better store or otherwise harness energy from vari-able natural resources. For instance, creatingsolar fuels(synthetic fuels produced from sunlight or solarheat) could allow us to capture solar energy when the sun is shining and then store this energy for lateruse. However, the process of discovering new materials can be slow and imprecise; the physics behindmaterials are not completely understood, so human experts often manually apply heuristics to understand aproposed material’s physical properties [75, 76]. ML techniques can automate this process by combiningexisting heuristics with experimental data, physics, and reasoning to apply and even extend existing physi-cal knowledge. For instance, recent work has used tools fromML, AI, optimization, and physics to figureout a proposed material’s crystal structure, with the goal of accelerating materials discovery for solar fuels[76–78]. Other work seeking to improve battery storage technologies has combined first-principles physicscalculations with support-vector regression to design conducting solids for lithium-ion batteries [79]. (Ad-ditional applications of ML to batteries are discussed in§2.3.)More generally in materials science, ML techniques including supervised learning, active learning, andgenerative models have been applied to the synthesis, characterization, modeling, and design of new andexisting materials, as described in reviews [75, 80] and more recent work [81]. As discussed in [75], novelchallenges for ML in materials science include coping with moderately sized datasets and producing inter-pretable predictions that shed light on the physical laws learned by a model; for example, the authors of [82]analyze the gradients of a convolutional neural network trained on materials data to understand the rules itlearned. ML can also help enable accelerated materials science by informing relevant innovation policies;for instance, previous work has applied NLP to patent data tounderstand the solar panel innovation process[83]. We note that while our focus here has been on electricity system applications, ML for acceleratedscience may also have significant impacts outside electricity systems, e.g. by helping design alternatives tocement (§4.2) or create better CO2sorbents (§6.2).Additional applicationsWhile the applications discussed above will likely providesome of the larger gains for variable low-carbonsources, there are a multitude of additional applications for ML in this space. For instance, it is important toensure that low-carbon variable generators capture ambient energy as efficiently as possible. Prior work hasattempted to maximize electricity production by controlling movable solar panels [84, 85] or wind turbineblades [86] using RL or Bayesian optimization. Other work has used graphical models to detect faults inrooftop solar panels [87], genetic algorithms to optimallyplace wind turbines within a wind farm [88], andmulti-objective optimization to place hydropower dams in away that satisfies both energy and ecologicalobjectives [89].ML can also help integrate rooftop solar panels into the electric grid, particularly in the United Statesand Europe. Rooftop solar panels are connected to a part of the electric grid called the distribution grid,which traditionally did not have many sensors because it wasonly used to deliver electricity “one-way”from centralized power plants to consumers. However, rooftop solar and otherdistributed energy resourceshave created a “two-way” flow of electricity on distributiongrids. Since the locations and sizes of rooftopsolar panels are not often known to electricity system operators, previous work has used computer visiontechniques on satellite imagery to generate size and location data for rooftop solar panels [90, 91]. Further,since electricity system operators need to ensure that the distribution system is stable despite lack of sensing,recent work has employed techniques such as matrix completion and deep neural networks for distributionsystem state estimation and forecasting [92–94].15https://powertac.org/8

1.1.2 Nuclear fission and fusionLow-carbon electricity sources such as nuclear fission and nuclear fusion can help achieve climate changegoals while requiring very few changes to how the electric grid is run. However, nuclear fission faces manypractical challenges, and nuclear fusion is not yet viable.ML can support these technologies by helpingmitigate some challenges faced by fission plants while helping accelerate the development of fusion plants.Nuclear power plantsSome argue that nuclear fission reactors (also known as nuclear power plants) are essential to meeting cli-mate change goals [95], but these technologies face significant challenges including public safety, wastedisposal, slow technological learning [96, 97], and high costs [95]. ML can help with a small piece ofthe latter problem by reducing maintenance costs; specifically, deep networks can speed up inspections bydetecting cracks and anomalies from image and video data [98] or by preemptively detecting faults fromhigh-dimensional sensor and simulation data [99]. The authors of [100] speculate that ML and high per-formance computing could also be used to help design next-generation nuclear reactors or simulate nuclearwaste disposal options.Nuclear fusionHigh LeverageLong-termHigh RiskNuclear fusion reactors16have the potential to produce safe and carbon-free electricity using a virtually lim-itless hydrogen fuel supply, but currently consume more energy than they produce [101]. While considerablescientific and engineering research is still needed, ML can help accelerate this work by guiding experimentaldesign and monitoring physical processes. Fusion reactorsrequire intelligent experimental design becausethey have a large number of tunable parameters; ML can help prioritize which parameter configurationsshould be explored during physical experiments. For instance, Google and TAE Technologies have devel-oped a human-in-the-loop experimental design algorithm enabling rapid parameter exploration for TAE’sreactor [102].Physically monitoring fusion reactors is also an importantapplication for ML. Modern reactors attemptto super-heat hydrogen into a plasma state and then stabilize it, but during this process, the plasma mayexperience rapid instabilities that damage the reactor. Prior work has tried to preemptively detect disruptionsfortokamakreactors, using supervised learning methods such as support-vector machines, adaptive fuzzylogic, decision trees, and deep learning [103–108] on previous disruption data. While many of these methodsare tuned to work on individual reactors, recent work has shown that deep learning may enable insights thatgeneralize to multiple reactors [108]. More generally, rather than simply detecting disruptions, scientistsneed to understand how plasma’s state evolves over time, e.g. by finding the solutions of time-dependentmagnetohydrodynamic equations [109]; speculatively, ML could help characterize this evolution and evenhelp steer plasma into safe states through reactor control.ML models for such fusion applications wouldlikely employ a combination of simulated17and experimental data, and would need to account for thedifferent physical characteristics, data volumes, and simulator speeds or accuracies associated with differentreactor types.1.2 Reducing current-system climate impactsWhile switching to low-carbon electricity sources will be essential, in the meantime, it will also be importantto mitigate emissions from the electricity system as it currently stands. Some methods for mitigating current-16For an overview of nuclear fusion, please see this collection of articles in Nature Physics:https://www.nature.com/collections/bccqhmkbyw.17Plasma simulation frameworks for tokamak reactors includeRAPTOR [110, 111], ASTRA [112], CRONOS [113], PTRANSP[114], and IPS [115].9

system impacts include cutting emissions from fossil fuels, reducing waste from electricity delivery, andflexibly managing demand to minimize its emissions impacts.Reducing life-cycle fossil fuel emissionsHigh LeverageReducing emissions from fossil fuel power generation is a necessary stop gap while society transitionstowards low-carbon electricity. In particular, ML can helpprevent the leakage of methane (an extremelypotent greenhouse gas) from natural gas pipelines and compressor stations. Previous and ongoing work hasused sensor and/or satellite data to proactively suggest pipeline maintenance [116]18or detect existing leaks(see [117], the SLED project,19and Bluefield Technologies20), and there is a great deal of opportunity in thisspace to improve and scale existing solutions. In addition to leak detection, ML can help reduce emissionsfrom freight transportation of solid fuels (§2) and may also have applications in the sequestration of CO2from power plant flue gas (§6.3). In all these cases, solutions should be pursued with great care so as not toimpede or prolong the transition to a low-carbon electricity system.Reducing system wasteAs electricity gets transported from generators to consumers, some of it gets lost as resistive heat on electric-ity lines. While some of these losses are unavoidable, others can be significantly mitigated to reduce wasteand emissions. ML can help prevent avoidable losses throughpredictive maintenance, i.e. by suggestingproactive electricity grid upgrades. Prior work has performed predictive maintenance using LSTMs [118],bipartite ranking [119], and neural network-plus-clustering techniques [120] on electric grid data, and futurework will need to improve and/or localize these solutions todifferent contexts.Modeling emissionsFlexibly managing household, commercial, industrial, andelectric vehicle demand (as well as energy stor-age) can help minimize electricity-based emissions (§2, 3, 4, 10), but doing so involves understanding whatthe emissions on the electric grid actually are at any moment. Specifically,marginal emissions factorscapture the emissions effects of small changes in demand at any given time. To inform consumers aboutmarginal emissions factors, WattTime21uses regression-based techniques to estimate these factors in realtime for the US, and the electricityMap project22employs ensemble models on electricity and weather datato forecast these factors a few days ahead for Europe. Great Britain’s National Grid ESO also uses ensemblemodels to forecastaverageemissions factors, which measure the aggregate emissions intensity of all powerplants.23There is still much room to improve the performance of these methods, as well as to forecastrelated quantities such as electricity curtailments (i.e.the wasting of usually low-carbon electricity for gridbalancing purposes). As most existing factor estimates arepoint estimates, it would also be important toquantify the uncertainty of these estimates to ensure that load-shifting techniques indeed decrease (ratherthan increase) emissions.18See alsohttps://www.oilandgaseng.com/articles/how-machine-learning-contributes-to-smarter-pipeline-maintenance/.19https://www.swri.org/press-release/swri-developing-methane-leak-detection-system-doe20http://bluefield.co/21https://www.watttime.org/22https://www.electricitymap.org23https://carbonintensity.org.uk/10

1.3 Empowering developing and low-data settingsMuch of the discussion around electricity systems often focuses on settings such as the United States withuniversal electricity access and relatively abundant data. However, many places that do not share theseattributes are still integral to the fight against climate change [26]. While ML applications for climatechange mitigation are largely uncharted in such places, they warrant serious consideration from the MLcommunity. Such applications in this area include improving electricity access and translating electricitysystem insights from data-abundant to low-data contexts.Improving electricity accessElectricity is critical to economic and social development, and can also help address climate change. Specif-ically, promoting clean electricity via electric grids,microgrids, or off-grid methods can displace dieselgenerators, wood-burning stoves, and other carbon-emitting electricity sources, and can also increase edu-cational outcomes [121, 122] (see§12). Figuring out what electrification methods are best for different areascan require intensive, boots-on-the-ground surveying work, but ML can help provide input to this processin a scalable manner; for instance, previous work has used image processing, clustering, and optimizationtechniques on satellite imagery as an input to planning electrification [123]. ML can also aid rural microgridoperation by accurately forecasting demand and power production (from e.g. solar panels), since small mi-crogrids are even harder to balance than country-scale electric grids; for example, recent work used a hybridLSTM and neural network architecture to model electricity load in rural microgrids [124]. Generating datato aid energy access policy and better managing energy access solutions are therefore two areas in whichML may have promising applications.Low-data settingsHigh LeverageWhile ML methods have often been applied to grids with widespread sensing, system operators in manycountries do not collect or share system data. Although these data availability practices may evolve, it maymeanwhile be beneficial to use techniques such as transfer learning to translate insights from data-abundantto low-data settings (especially since all electric grids share the same underlying system physics). Low-dataML techniques may also be beneficial in this setting; for instance, in [125], the authors enforce physical orother domain-specific constraints on weakly supervised ML models, allowing these models to learn fromvery little labeled data. ML techniques can also help generate information about low-data settings. Forinstance, recent work has used satellite image recognition(along with graph search techniques) to estimatethe layout of electricity grids in regions where they may notbe explicitly mapped [126], and companieshave also proposed to use satellite imagery to measure power plant CO2 emissions24(also see§5.1). Otherrecent work has used regression-based techniques on cellular network data to model electricity consumption[127], which may prove useful in settings with many cellulartowers but few electric grid sensors. Although low-data settings are generally under-explored by the ML community, electricity systems research in these settings presents a great opportunity for both ML and climate change.

2 Transportationby Lynn H. KaackTransportation systems form a complex web that is fundamental to an active and prosperous society. Overall,the transportation sector accounts for about a quarter of global energy-related CO2emissions [4]. In contrastto the electricity sector, transportation has not made significant progress to lower its CO2emissions [131]and much of the transportation sector is regarded as hard to decarbonize [132]. This is because of the highenergy density of fuels required for many types of vehicles,which constrains low-carbon alternatives, andbecause transport policies directly impact end-users and are thus more likely to be controversial.Passenger and freight transportation are each responsiblefor about half of transport GHG emissions[133]. Both freight and passengers can travel by road, by rail, by water, or by air (referred to astransportmodes). Different modes carry vastly different carbon emission intensities.25At present, more than two-thirds of transportation emissions are from road travel [133], but air travel has the highest emission intensityand is responsible for an increasingly large share. Strategies to reduce GHG emissions26from transportationinclude [133]:•Decreasing transportation activity.•Increasing vehicle efficiency.•Reducing the carbon impact of fuel.•Shifting to lower-carbon options, like rail.Each of these mitigation strategies offers opportunities for ML. While many of us probably think of au-tonomous vehicles and shared mobility when we think of transport and ML, these technologies can help toreduce but also might increase GHG emissions [137]. Here, wediscuss these disruptive technologies (§2.1)but show that ML can play a role for decarbonizing transportation that goes much further. ML can improvevehicle engineering, enable intelligent infrastructure,and provide policy-relevant information. Many inter-ventions that reduce GHG emissions in the transportation sector require changes in planning, maintenance,and operations of transportation systems, even though the GHG reduction potential of those measures mightnot be immediately apparent. ML that is concerned with improving these tasks, for example by providingbetter demand forecasts, can make transportation more efficient. Typically, ML solutions are most effectivein tandem with strong public policies. While we do not cover all ML applications in the transportationsector, we aim to include those areas which can conceivably reduce GHG emissions.2.1 Reducing transport activityA colossal amount of transport occurs each day across the world, but much of this mileage is used ineffi-ciently, resulting in needless GHG emissions. With the helpof ML, the number of vehicle-miles traveled canbe reduced by making long trips less necessary, increasing loading, and optimizing vehicle routing. Here,we discuss the first two in depth – for a discussion of ML and routing, see for example [138].Understanding transportation dataMany areas of transportation lack data, and decision-makers often plan infrastructure and policy based onuncertain information. In recent years, new types of sensors have become available, and ML can providerelevant information from these data. Traditionally, traffic is monitored with ground-based counters that areinstalled on a selected number of roads. A variety of technologies are used, such as inductive loop detectors25Carbon intensity is measured in grams of CO2-equivalent per person-km or per ton-km, respectively.26For general resources on how to decarbonize the transportation sector, see the AR5 chapter on transportation [133], and[134–136].13

or pneumatic tubes. In particular when counting pedestrians and cyclists, traffic is monitored with videosystems, which can be automated with computer vision [139].Since counts on most roads are often avail-able only over short time frames, these roads are modeled by looking at known traffic patterns for similarroads. ML methods, such as SVMs and neural networks, have made it easier to classify roads with simi-lar traffic patterns [140–142]. As ground-based counters require costly installation and maintenance, manycountries do not have such systems. Vehicles can also be detected in high-resolution satellite images withhigh accuracy [143–146], and image counts can serve to estimate average vehicle traffic [147]. Similarly,ML methods can help with imputing missing data for precise bottom-up estimation of GHG emissions [148]and they are also applied in simulation models of vehicle emissions [149].Modeling demandHigh LeverageBy discouraging sprawl and creating new transportation links, modeling demand and planning new infras-tructure can significantly shape how long trips are and whichtransport modes are chosen by passengers andshippers. ML can provide information about mobility patterns – which is directly necessary for agent-basedtravel demand models, one of the main transport planning tools [150]. For example, ML makes it possible toestimate origin-destination demand from traffic counts [151], and it offers new methods for spatio-temporalroad traffic forecasting – which do not always outperform other statistical methods [152] but may transferwell between areas [153]. Also, short-term forecasting of public transit ridership can improve with ML; seefor example [154, 155]. ML is particularly relevant for deducing information from novel data – for example,learning about the behavior of public transit users from smart card data [156, 157]. Also, mobile phone sen-sors provide new means to understand personal travel demandand the urban topology, such as walking routechoices [158]. Similarly, ML-based modeling can help to mitigate climate change by improving operationalefficiency of modes that emit significant CO2. In the aviation sector, interventions that reduce aircraft taxitime and congestion on the runway bring fuel consumption down [159]. ML can help, for example, bypredicting taxi time for efficient runway scheduling [160].Shared mobilityHigh RiskIn the passenger sector, shared mobility (such as on-demandride services or vehicle-sharing27), is undoubt-edly disrupting the way people travel and think about vehicle ownership, and ML plays an integral part inoptimizing these services (e.g. [161]). However, it is largely unclear what the impact of this developmentwill be. For example, shared cars can actually cause more people to travel by car, as opposed to usingpublic transportation. Similarly, on-demand taxi services add mileage when traveling without a customer,possibly negating any GHG emission savings [162]. On the other hand, shared mobility can lead to higherutilization of each vehicle, which means a more efficient useof materials [163]. The use of newer andmore efficient vehicles, ideally electric ones, could increase with vehicle sharing concepts, reducing GHGemissions. Some of the issues raised above could also perhaps be overcome by making taxis autonomous.Such vehicles also might integrate better with public transportation, and offer new concepts for pooled rides,which substantially reduce the emissions per person-mile.ML methods can help to understand the energy impact of sharedmobility concepts, for example whatresults in more energy-efficient customer behavior, such asride sharing [164]. It would also be very impor-tant for decision-makers to have access to timely location-specific empirical analysis to understand if a rideshare service is taking away customers from low-carbon transit modes and increasing the use of cars.Car-sharing services using autonomous vehicles could yield GHG emission savings when they encour-age people to use public transit for part of the journey [165]or with autonomous electric vehicles [166].However, using autonomous shared vehicles alone could increase the total vehicle-miles traveled and there-fore do not necessarily lead to lower emissions when based oninternal combustion engines (or electrical27In this section, we discuss shared cars; see§2.4 for bike shares and electric scooters.14

vehicles and a “dirty” electrical grid) [167, 168]. We see the intersection of shared mobility, autonomousand electric vehicles, and smart public transit as a path where ML can make a contribution to shaping futuremobility. See also§2.2 for more on autonomous vehicles.When designing and promoting new mobility services, industry and public policy should prioritize low-ering GHG emissions. Misaligned incentives in the early stages of technological development could resultin the lock-in to a service with high GHG emissions [169, 170].Freight routing and consolidationHigh LeverageBundling shipments together, which is referred to as freight consolidation, dramatically reduces the num-ber of trips (and therefore GHG emissions). The same is true for changing routing so that trucks do nothave to return empty. As rail and water modes require much larger loads than trucks, consolidation alsoenables shipments to use these modes for part of the journey [147]. Freight consolidation and routing de-cisions are often taken by third-partylogistics service providersand other freight forwarders, such as inthe less-than-truckload market, which deals with shipments of smaller sizes. ML offers opportunities tooptimize this complex interaction of shipment sizes, modes, origin-destination pairs, and service require-ments. There are many proposed and deployed solutions usingML, for example predicting arrival times ordemand, identifying and planning around transportation disruptions [171], or clustering suppliers by theirgeographical location and common shipping destinations. Designing allocation algorithms and freight auc-tions are proposed planning approaches, and ML has for example been shown to help pick good algorithmsand parameters to solve auction markets [172].Alternatives to transportHigh RiskDisruptive technologies that are based on ML could replace or reduce transportation demand. For example,additive manufacturing (AM, or 3-D printing) has (limited)potential to reduce freight transport by producinglighter goods and enabling production closer to the consumer [136]. ML can be a valuable tool for improvingAM processes [173]. ML can also help to improve virtual communication [174]. If passenger trips arereplaced by telepresence, travel demand can be reduced, as has been shown for example in public agencies[175] and for scientific teams [176]. However, it is uncertain to what extent virtual meetings replace physicaltravel, or if they may actually give rise to more face-to-face meetings [177].2.2 Vehicle efficiencyMost vehicles are not very efficient compared to what is technically possible: for example, through fleetturnover alone, aircraft carbon intensity can decline by more than a third with respect to 2012 [178]. Boththe design of the vehicle and the way it is operated can increase the fuel economy. Here, we discuss howML can help constructing more efficient vehicles and what kind of impact autonomous driving could haveon GHG emissions. Encouraging drivers to adopt more efficient vehicles is also a priority; while we do notfocus on this here, ML plays a role in studying consumer preferences in vehicle markets [179].Designing for efficiencyThere are many ways to reduce the energy a vehicle uses – such as more efficient engines, improved aero-dynamics, hybrid electric engines, and reducing the vehicle’s weight or tire resistance. These differentstrategies require a broad range of engineering techniques, many of which can benefit from ML. For exam-ple, ML is applied in advanced combustion engine design [180]. Hybrid electric vehicles, which are moreefficient than combustion engines alone, rely on power management methods that can be improved withML [181]. Aerodynamic efficiency improvements need turbulence modeling that is often computationallyintensive and relies heavily on ML-based surrogate models [182]. Aerodynamic improvements can not only15

be made by vehicle design but also by rearranging load. Lai etal. [183] use computer vision to detectaerodynamically inefficient loading on freight trains. Additive manufacturing (3-D printing) can producelighter parts in vehicles, such as road vehicles and aircraft, that reduce energy consumption [147, 163]. MLis applied to improve those processes, for example through failure detection [184, 185] or material design[186].Autonomous vehiclesHigh RiskMachine learning is essential in the development of autonomous vehicles (AVs), including in such basictasks as following the road and detecting obstacles [187].28While AVs could reduce energy consumption– for example, by reducing traffic congestion and inducing eco-driving – it is also possible that AVs willlead to an increase in overall road traffic that nullifies efficiency gains. (For an overview of possible energyimpacts of AVs see [137, 188] and for broader impacts on mobility see [189].) Two advantages of AVs in thefreight sector promise to cut GHG emissions: First, small autonomous vehicles, such as delivery robots anddrones, could reduce the energy consumption of last-mile delivery [190], though they come with regulatorychallenges [191]. Second, trucks can reduce energy consumption byplatooning(driving very close togetherto reduce air resistance), thereby alleviating some of the challenges that come with electrifying long-distanceroad freight [192]. Platooning relies on autonomous driving and communication technologies that allowvehicles to brake and accelerate simultaneously.ML can help to develop AV technologies specifically aimed at reducing energy consumption. For ex-ample, Wu et al. [193, 194] develop AV controllers based on reinforcement learning to smooth out trafficinvolving non-autonomous vehicles, reducing congestion-related energy consumption. ML methods canalso help to understand driving practices that are more energy efficient. For example, Jim ́enez et al. [195]use data from smart phone sensors to identify driving behavior that led to higher energy consumption inelectric vehicles.2.3 Alternative fuels and electrificationElectric vehiclesHigh LeverageElectrifying vehicles is regarded as a primary means to decarbonize transport. Electric vehicle (EV) tech-nologies rely on batteries, hydrogen fuel cells, or electrified roads and railways, and can have very low GHGemissions – assuming, of course, that the electricity is generated with mostly low-carbon generators. MLis vital for a range of different problems related to EVs. Rigas et al. [196] detail methods by which MLcan improve charge scheduling, congestion management, andvehicle-to-grid algorithms. ML methods havealso been applied to battery energy management (for examplecharge estimation [197] or optimization inhybrid EVs [181]), and to detect faults and lateral misalignment in wireless charging of EVs [198].As more people drive EVs, understanding their use patterns will become more important. Modelingcharging behavior will be useful for grid operators lookingto predict electric load. For this application, it ispossible to analyze residential EV charging behavior from aggregate electricity load (energy disaggregation,see also§3.1) [199]. Also, in-vehicle sensors and communication data are increasingly becoming availableand offer an opportunity to understand travel and charging behavior of EV owners, which can for exampleinform the placement of charging stations [200].Battery electric vehicles are typically not used for more than a fraction of the day, allowing them to act asenergy storage for the grid at other times, where charging and discharging is controlled for example by pricesignals [201] (see§1.1.1,1.2). There is much potential for ML to improve such vehicle-to-grid technology,for example with reinforcement learning [202], which can reduce GHG emissions from electricity genera-tion. Vehicle-to-grid technology comes with private and social financial benefits. However, consumers are28Providing details on the role of ML for AVs is beyond the scopeof this paper.16

expected to be reluctant to agree to such services, as they might not want to compromise their driving range[203].Finally, ML can also play a role in the research and development of batteries, a decisive technologyfor EV costs and usability. Work in this area has focused on predicting battery state, degradation, andremaining lifetime using supervised learning techniques,fuzzy logic, and clustering [204–211]. However,many models developed in academia are based on laboratory data that do not account for real-world factorssuch as environmental conditions [204–206]. By contrast, industry lags behind in ML modeling, but real-world operational data are readily available. Merging these two perspectives could yield significant benefitsfor the field.Alternative fuelsLong-termHigh RiskMuch of the transportation sector is highly dependent on liquid fossil fuels. Aviation, long-distance roadtransportation, and ocean shipping require fuels with highenergy density and thus are not conducive to elec-trification [132]. Electrofuels [212], biofuels [213], hydrogen [214, 215], and perhaps natural gas [216] offeralternatives, but the use of these fuels is constrained by factors such as cost, land-use, and (for hydrogen andnatural gas) incompatibility with current infrastructure[132]. Electrofuels and biofuels have the potential toserve as low-carbon drop-in fuels that retain the properties of fossil fuels, such as high energy density, whileretaining compatibility with the existing fleet of vehiclesand the current fuel infrastructure [147]. Fuelssuch as electrofuels and hydrogen can be produced using electricity-intensive processes and can be stored atlower cost than electricity. Thus, these fuels could provide services to the electricity grid by using electricityflexibly and balancing variable electricity generators (§1.1.1). Given their relative long-term importance andearly stage of development, they present a critical opportunity to mitigate climate change. ML techniquesmay present opportunities for improvement at various stages of research and development of alternativefuels (similar to applications in§1.1.1).2.4 Modal shiftShifting passengers and freight to low carbon-intensity modes is one of the most important means to de-carbonize transport. Thismodal shiftin passenger transportation can for example involve providing peoplewith public transit, which requires analyzing mode choice and travel demand data. ML can also make lowcarbon-intensive freight modes more competitive by helping to coordinate intermodal transport.Passenger preferencesML can improve our understanding about passengers’ travel mode choices, which in turn informs transporta-tion planning, such as where public transit should be built.Some recent studies have shown that supervisedML based on survey data can improve passenger mode choice models [217–219]. Seo et al. propose toconduct long-term travel surveys with online learning, which reduces the demand on respondents, whileobtaining high data quality [220]. Sun et al. [221] use SVMs and neural networks for analyzing preferencesof customers traveling by high speed rail in China. There is also work on inferring people’s travel modesand destinations from social media or various mobile phone sensors such as GPS (transportation mode de-tection), e.g. [222, 223]. Also in the freight sector, ML has been applied to analyze modal trade-offs, forexample by imputing data on counterfactual mode choices [224]Improving low-carbon optionsHigh LeverageIn order to incentive more users to choose low-carbon transport modes, their costs and service quality canbe improved. Many low-carbon modes must be integrated with other modes of transportation to deliver thesame level of service. For example, when traveling by train,the trip to and from the station will often be17

by car, taxi, bus, or bike. There are many opportunities for ML to facilitate a better integration of modes,both in the passenger and freight sectors. ML can also help toimprove the operation of low-carbon modes,for example by reducing the operations and maintenance costs of rail [225] and predicting track degradation[226].Bike sharing and electric scooter services can offer low-carbon alternatives for urban mobility that donot require ownership and integrate well with public transportation. ML studies help to understand howusage patterns for bike stations depend on their immediate urban surroundings [227]. ML can also helpsolve the bike sharing rebalancing problem by improving forecasts of bike demand and inventory [228].Singla et al. [229] propose a pricing mechanism based on online learning to provide monetary incentives forbike users to help rebalancing. By producing accurate travel time estimates, ML can provide tools that helpto integrate bike shares with other modes of transportation[230]. Many emerging bike and scooter sharingservices are dockless, which means that they are parked anywhere in public space and can block sidewalks[231]. ML has been applied to monitor public sentiment aboutsuch bike shares via tweets [232]. ML couldalso provide tools and information for regulators to ensurethat public space can be used by everyone [233].Coordination between modes resulting in faster and more reliable transit times could increase the amountof people or goods traveling on low-carbon modes such as rail. ML algorithms could be applied to makepublic transportation faster and easier to use. For example, there is a rich literature exploring ML methodsto predict bus arrival times and their uncertainty [234, 235]. Often freight is packaged so that it can switchbetween different modes of transport easily. Suchintermodaltransportation relies on low-carbon modessuch as rail and water for part of the journey [136]. ML can provide solutions by improving predictions ofthe estimated time of arrival (for example of freight trains[236]) or the weight or volume of expected freight(for example for roll-on/roll-off transport – often abbreivated as Ro-Ro [237]). Intelligent transport systemsof different modes could be combined and enable more efficient multimodal freight transportation [136].Lax enforcement of regulation can make modes with high GHG emissions, such as trucks, competitive[136]. ML can assist public institutions with enforcing their regulations. For example, image recognitioncan help law enforcement detect overloading of trucks

3 Buildings & Citiesby Nikola Milojevic-Dupont and Lynn H. KaackBuildings offer some of the lowest-hanging fruit when it comes to reducing GHG emissions. While the en-ergy consumed in buildings is responsible for a quarter of global energy-related emissions [4], a combinationof easy-to-implement fixes and state-of-the-art solutions29could reduce emissions for existing buildings by90% [240]. It is possible today for buildings to consume almost no energy [241].30Many of these energyefficiency measures actually result in overall cost savings[242] and simultaneously yield other benefits, suchas cleaner air for occupants. This potential can be achievedwhile maintaining the services that buildingsprovide – and even while extending them to more people, as climate change will necessitate. For example,with the changing climate, more people will need access to air conditioning in regions where deadly heatwaves will become common [243, 244].Two major challenges are heterogeneity and inertia. Buildings vary according to age, construction,usage, and ownership, so optimal solutions vary widely depending on the context. For instance, buildingswith access to cheap, low-carbon electricity may have less need for expensive features such as intelligentlight bulbs. Buildings also have very long lifespans; thus,it is necessary both to create new, energy-efficientbuildings, and to retrofit old buildings to be as efficient as possible [245]. Urban planning and public policycan play a major role in reducing emissions by providing infrastructure, financial incentives, or energystandards for buildings.31Machine learning provides critical tools both for managingbuildings and for designing policies sur-rounding them. At the level of building management, ML can help select solutions that are tailored toindividual buildings, and can also contribute to implementing those solutions via smart control systems(§3.1). At the level of urban planning, ML can be used to gather and make sense of data to inform policymakers (§3.2).323.1 Optimizing buildingsIn designing new buildings and improving existing ones, there are numerous technologies that can reduceboth costs and GHG emissions. ML can accelerate these solutions by (i) modeling data on energy consump-tion and (ii) optimizing energy use (insmart buildings).Energy use modelsAn essential step towards efficiency is making sense of the increasing amounts of data produced by metersand home energy monitors.33This can take the form of energy demand forecasts for individual build-ings, which are useful both for power companies (§1.1.1) and in evaluating building design and operationstrategies [246]. Traditional energy demand forecasts model the physical structure of a building, and areessentially massive thermodynamics computations. ML has the potential to speed up these computationsgreatly, either by ignoring physical knowledge of the building entirely [247, 248], by incorporating it intothe computation [249], or by learning to approximate the physical model to reduce the need for expensive29The IPCC classifies mitigation actions in buildings into four categories:carbon efficiency(switching to low-carbon fuels or tonatural refrigerants);energy efficiency(reducing energy waste through insulation, efficient appliances, better heating and ventilation,or other similar measures);system and infrastructure efficiency(e.g. passive house standards, urban planning, and district coolingand heating); andservice demand reduction(behavioral and lifestyle changes) [239].30There are even high-rise buildings, e.g. the Tower Raiffeisen-Holding N ̈O-Vienna office, or large university buildings, e.g. theTechnical University also in Vienna, that achieve such performance.31For example, see the case of New York City, which mandated that building owners collectively reduce their emissions by 40%by 2040:https://www.nytimes.com/2019/04/17/nyregion/nyc-energy-laws.html.32For example, the startup nam.R is developing a database of all school buildings in France, harmonizing vast amounts of openand proprietary data with ML. See project tRees athttps://namr.com/#.33For example, seehttps://sense.com.19

simulation (surrogate models) [250]. Learning how to transfer the knowledge gained from modeling onebuilding to another can make it easier to render precise estimations of more buildings. For instance, Mocanuet al. [251] modeled building load profiles with reinforcement learning and deep belief networks using dataon commercial and residential buildings; they then used approximate reinforcement learning and transferlearning to make predictions about new buildings, enablingthe transfer of knowledge from commercial toresidential buildings, and from gas- to power-heated buildings.Within a single building, understanding which appliances drive energy use (energy disaggregation) iscrucial for targeting efficiency measures and enabling behavioral changes. Promising ML approaches tothis problem include hidden Markov models [252], sparse coding algorithms for structured prediction [253],harmonic analysis that picks out the “signatures” of individual appliances [254], and deep neural networks[255].To verify the success or failure of energy efficiency interventions, statistical ML offers methods forcausal inference. For example, Burlig et al. [256] used Lasso regression on hourly electricity consumptiondata from schools in California to find that energy efficiencyinterventions fall short of the expected savings.Such problems could represent a useful application of deep learning methods for counterfactual prediction[257].Smart buildingsHigh LeverageIntelligent control systems in buildings can decrease the carbon footprint both by reducing the energy con-sumed and by providing means to integrate lower-carbon sources into the electricity mix [258]. Specifically,ML can reduce energy usage by allowing devices and systems toadapt to usage patterns. Further, buildingscan respond to signals from the electricity grid, providingflexibility to the grid operator and lowering coststo the consumer (§1.1.1).Many critical systems inside buildings can be made radically more efficient. While this is also true forsmall appliances such as refrigerators and lightbulbs, we use the example of heating and cooling (HVAC)systems, both because they are notoriously inefficient and because they account for more than half of theenergy consumed in buildings [239]. There are several promising ways to enhance HVAC operating per-formance, each providing significant opportunities for using ML: forecasting what temperatures are neededthroughout the system, better control to achieve those temperatures, and fault detection. Forecasting temper-atures, as with modeling energy use in buildings, has traditionally been performed using detailed physicalmodels of the system involved; however, ML approaches such as deep belief networks can potentially in-crease accuracy with less computational expense [259, 260](see also§4.3). For control, Kazmi et al. [261]used deep reinforcement learning to achieve a scalable 20% reduction of energy while requiring only threesensors: air temperature, water temperature, and energy use (see also§4.3 for similarly substantial gainsin datacenter cooling). Finally, ML can automate building diagnostics and maintenance through fault-detection. For example, the energy efficiency of cooling systems can degrade if refrigerant levels are low[262]; ML approaches are well-suited to detect faults in these systems. Wang et al. [263] treated HVACfault-detection as a one-class classification problem, using only temperature readings for their predictions.Deep autoencoders can be used to simplify information aboutmachine operation so that deep neural net-works can then more easily predict multiple kinds of faults [264].Many systems within buildings – such as lights and heating – can also adjust how they operate basedon whether a building or room is occupied, thereby improvingboth occupant comfort and energy use [265].ML can help these systems dynamically adapt to changes in occupancy patterns [266]. Moreover, occupancydetection itself represents an opportunity for ML algorithms, ranging from decision trees [267, 268] to deepneural networks [269] that take input from occupancy sensors [267], WiFi signals [269, 270], or appliancepower consumption data [268].In§1.1.1, we discussed how using variable low-carbon energy can mean that the supply and price of20

electricity varies over time. Thus, energy flexibility in buildings is increasingly useful to schedule consump-tion when supply is high [271]. For this, automated demand-side response [272] can respond to electricityprices, smart meter signals, or learned user preferences [273]. Edge computing can be used to process datafrom distributed sensors and otherInternet of Thingsdevices, and deep reinforcement learning can then usethis data to efficiently schedule energy use [274].While smart building technologies have the capability to significantly increase efficiency, we should notethat there are potential drawbacks [275]. First, smart building devices and connection networks, like wirelesssensor networks, consume energy themselves; however, deepneural networks can be used to monitor andoptimize their operations [276]. Second, rebound effects are likely to happen in certain cases [277], leadingto additional consumption typically ranging between 10 and20% [278] for buildings in general. If controlsystems optimize for costs, interventions do not necessarily translate into energy efficiency measures orGHG reductions. Therefore, public policies are needed to mandate, support and complement actions forindividual building managers [239]. Another concern in case of widespread adoption of smart meters is theimpact on mineral use and embodied energy use arising from their production [279]. Finally, smart homeapplications present security and privacy risks [280] thatrequire adequate regulation.3.2 Urban planningFor many impactful mitigation strategies – such as districtheating and cooling, neighborhood planning,and large-scale retrofitting of existing buildings – coordination at the district and city level is essential.Policy-makers use instruments such as building codes, retrofitting subsidies, investments in public utilities,and public-private partnerships in order to reduce GHG emissions without compromising equity. Whileinfrastructure models have yet to be adopted at scale, they can be highly impactful in informing policymakers about heterogeneities among buildings, the energy impact of policies, and aggregated GHG emissionestimates and forecasts. This can for example be used for planning and operatingdistrict heating andcooling, where a central plant supplies many households in a district. District heating and cooling reducesHVAC energy consumption and can provide flexible load [281],but it needs large amounts of data at thedistrict level for implementation and operation.However, district-level data is often not available. ML canhelp in obtaining it in two ways: Whereenergy-use data on individual buildings exists, ML can be used to derive higher-level patterns. Where dataon energy use and infrastructure is completely lacking, ML can infer it.District-level energy useBottom-up multi-building energy models are expected to become fundamental for enabling localized actionby city planners [282]. ML can learn from available energy use data to extrapolate building energy usepredictions to the city level. Based on energy data disclosed by residents of New York City, Kontokostaand colleagues used various ML methods to predict the energyuse of the city’s 1.1 million buildings [283],analyzed the effect of energy disclosure on the demand [284], and developed a system for ranking build-ings based on energy efficiency [285]. Zhang et al. [286] matched residential energy consumption surveydata with public use microdata samples to estimate residential energy consumption at the neighborhoodlevel. Robinson et al. [287] showed that using a simple gradient boosting technique can predict commercialbuilding energy use across large American cities, using simple features of individual buildings.Gathering infrastructure dataHigh LeverageMany regions of the world have almost no energy consumption data, which can make it difficult to designtargeted mitigation strategies. ML is uniquely capable of predicting energy consumption and GHG miti-gation potential at scale from other types of available data. Information about building footprint, usage,material, roof type, immediate surroundings etc. can be predictive of energy consumption. For example,21

Kolter and Ferreira used Gaussian process regression to predict energy use from features such as propertyclass or the presence of central AC [288]. ML can be used to pinpoint which buildings have the highestretrofit potential using simple building characteristics and surrounding environmental factors [289, 290] –both potentially available at scale.Specifics about building infrastructure can also often be predicted using ML techniques, providing datafor energy planning. Remote sensing is key to this process [91, 291–295] as satellite data34offers a source ofinformation that is globally available and largely consistent worldwide. For example, using remote sensingdata, Geiß et al. [297] clustered buildings into types to assess the potential of district heat in a German town.The resolution of infrastructure models ranges from coarselocalization of all buildings at the globalscale [291], to precise 3D reconstruction of a neighborhood[295]. It is possible to produce a global mapof human settlement footprints at meter-level resolution from satellite radar images [291]. For this, Esch etal. used highly automated learners, which make classification at such scale possible by retraining locally.Segmentation of high-resolution satellite images can now generate exact building footprints at a nationalscale [292]. Energy-relevant building attributes, such asthe presence of photovoltaic panels, can also beretrieved from these images [91] (see§1.1.1). To generate 3D models, LiDAR data is often used to retrieveheights or classify buildings at city scale [293, 294], but its collection is expensive. Recent research showedthat heights can be predicted even without such elevation data, as demonstrated by [298], who predictedthese from real estate records and census data. Studies, which for now are small scale, aim for complete 3Dreconstruction with class labels for different componentsof buildings [295].3.3 The future of citiesSince most of the resources of the world are ultimately channeled into cities, municipal governments havea unique opportunity to mitigate climate change. City governments regulate (and sometimes operate) trans-port, buildings, and economic activity. They take care of such diverse issues as water, waste, energy, crime,health, and noise. Recently, data and ML have become more common for improving efficiency in such areas,giving rise to the notion ofsmart city. While the phrasesmart cityencompasses a wide array of technologies[299], here we discuss only applications that are relevant reducing GHG emissions.Data for smart citiesIncreasingly, important aspects of city life come with digital information that can make the city function ina more coordinated way. Habibzadeh et al. [300] differentiate betweenhard-sensing, i.e., fixed-location-dedicated sensors like traffic cameras, andsoft-sensing, for example from mobile devices. Hard sensing isthe primary data collection paradigm in many smart city applications, as it is adapted to precisely meet theapplication requirements. However, there is a growing volume of data coming from soft sensing, due to thewidespread adoption of personal devices like smartphones that can provide movement data and geotaggedpictures.35Jiang provides a review of urban computing for mobile phone traces [302]. Relevant informationon the urban space can also be learned from social media activity, like Twitter, as reviewed in [303, 304].There are, however, numerous obstacles to making sense of this wealth of data (see [305]).First, cities need to obtain relevant data on activities that directly or indirectly consume energy. Dataare often proprietary. To obtain these data, the city of Los Angeles now requires allmobility as a serviceproviders, i.e. vehicle-sharing companies, to use an open-source API. Data on location, use, and conditionof all those vehicles, which can be useful in guiding regulation, are thus transmitted to the city [306]. MLcan also distill information on urban issues related to climate change through web-scraping and text-mining,e.g. [232]. As discussed above (§3.2), ML can also be used to infer infrastructure data.34See [296] for a review of different sources of data and deep learning methods for processing them.35Note that management of any such private data, even if they are anonymized, poses challenges [301].22

Second, smart city applications must transmit high volumesof data in real-time. ML is key to prepro-cessing large amounts of data in large sensor networks, allowing only what is relevant to be transmitted,instead of all the raw data that is being collected [307–309]. Similar techniques also help to reduce theamount of energy consumed during transmission itself [310].Third, urban policy-making based on intelligent infrastructure faces major challenges with data man-agement [311]. Smart cities require the integration of multiple large and heterogeneous sources of data, forwhich ML can be a valuable tool, which includes data matching[312, 313], data fusion [314], and ensemblelearning [315].Low-emission infrastructureHigh LeverageWhen smart city projects are properly integrated into urbanplanning, they can make cities more sustainableand foster low-carbon lifestyles (see [310, 316, 317] for extensive reviews on this topic). Because of thefeedback between different sectors, many mitigation options need to be planned by one entity – the localgovernment. For instance, urban sprawl influences the energy use from transport, as wider cities tend to bemore car-oriented [318–320]. ML-based analysis has shown that the development of efficient public trans-portation is dependent on both the extent of urban sprawl andthe local development around transportationhubs [321, 322]. This shows how much buildings influence transportation systems, and vice versa.Cities also can reduce GHG emissions by coordinating between infrastructure sectors and better adaptingservices to the needs of the inhabitants. Smart applications based on ML and AI can coordinate, for example,district heating and cooling networks, solar power generation, and charging stations for electric vehicles andbikes [317]. ML predictions are often useful, e.g. for improving public lighting systems by regulating lightintensity based on historical patterns of foot traffic [323]. Due to inherent variability in energy demand andsupply, there is a need for uncertainty estimation, e.g. using Markov chain Monte Carlo methods or Gaussianprocesses [317].Currently, most smart city projects for urban climate change mitigation are implemented in wealthierregions such as the United States, China, and the EU.36The literature on city-scale solutions is also stronglybiased towards the global North [324], while key mitigationchallenges are expected to arise from the globalSouth [325]. Infrastructure models described in§3.2 could be used to plan low-carbon neighborhoods with-out relying on advanced smart city technologies. To transfer solutions across cities, it is possible to clustersimilar cities based on climate-relevant dimensions [319,326, 327]. Creutzig et al. [319], for example, re-lated the energy use of 300 cities worldwide to historical structural factors such as fuel taxes (which havea strong impact on urban sprawl). Other relevant applications include groupings of transportation systems[326] using a latent class choice model, or of street networks [327] to identify common patterns in urbandevelopment using hierarchical clustering.

4 Industryby Anna Waldman-BrownIndustrial production, logistics, and building materialsare leading causes of difficult-to-eliminate GHGemissions [132]. Luckily for ML researchers, the global industrial sector spends billions of dollars annuallygathering data on factories and supply chains [329] – aided by improvements in the cost and accessibility ofsensors and other data-gathering mechanisms (such as QR codes and image recognition). The availabilityof large quantities of data, combined with affordable cloud-based storage and computing, indicates thatindustry may be an excellent place for ML to make a positive climate impact. ML researchers can potentiallyreduce global emissions by helping to streamline supply chains, improve production quality, predict machinebreakdowns, optimize heating and cooling systems, and prioritize the use of clean electricity over fossil fuels[330–333].Nonetheless, two key challenges stand in the way of harnessing ML for GHG mitigation within industry.Most importantly, the Jevons paradox indicates that efficiency increases may lead to rebound effects, result-ing in increased goods production with even greater GHG emissions unless industrial actors have sufficientincentives to reduce overall emissions [334]. Secondly, despite the proliferation of industrial data, much ofthe information is proprietary, low-quality, or very specific to individual machines or processes; practitionersestimate that 60-70% of industrial data goes unused [329, 335]. Before investing in extensive ML research,researchers should be sure that they will be able to eventually access and clean any data needed for theiralgorithms.4.1 Supply chainsHigh LeverageIn 2006, at least two Scottish seafood firms flew hundreds of metric tons of shrimp from Scotland to Chinaand Thailand for peeling, then back to Scotland for sale – because they could save on labor costs [336].This indicates the complexity of today’s globalized supplychains, defined as the processes and systems oforganizations and the shipping networks that are required to bring a product from producer to final consumer.While ML can help minimize emissions by optimizing shippingroutes§2.1, reducing waste, and helpingfirms identify local producers and suppliers, firms’ financial incentives must also align with climate changemitigation through carbon pricing or other policy mechanisms. ML could reduce emissions in supply chainsby intelligently predicting supply and demand, identifying lower-carbon products, and optimizing shippingroutes. For details on shipping and delivery optimization,see§2.The production, shipment, and climate-controlled warehousing of excess products is a major source ofindustrial GHG emissions, particularly for time-dependent goods such as perishable food or retail goods thatquickly fall out of fashion [337]. In 2011, a survey of corporate sales estimates diverged from actual salesby an average of 40%, and the Council of Supply Chain Management Professionals estimated global excessinventory to be $8 trillion worth of goods [338]. ML may be able to mitigate these issues of overproducingand/or overstocking goods by improving demand forecasting[339, 340]. For example, the clothing industrysells an average of only 60% of its wares at full price, but some brands can sell up to 85% due to just-in-timemanufacturing and clever intelligence networks [341]. As online shopping and just-in-time manufacturingbecome more prevalent and websites offer more product typesthan physical storefronts, better demandforecasts will be needed on a regional level to efficiently distribute inventory without letting unwantedgoods travel long distances only to languish in warehouses [342]. Nonetheless, negative side effects canbe significant depending on the type of product and regional characteristics; just-in-time manufacturing andonline shopping are often responsible for smaller and faster shipments of goods, mostly on road, that lackthe energy efficiency of freight aggregation and slower shipping methods such as rail [342, 343].For ML to help reduce supply chain emissions, industry will need to make substantial improvements indata as well as more domain-specific models, such as task-based deep learning frameworks that could allowfor the prediction of demand to specifically reduce the cost (or GHG emissions) associated with inventory24

stocking [58]. Firms may then be able both to manufacture fewer products overall and to minimize theGHG needed for climate control during storage. Researchersare training deep learning systems to minimizecounterfactual prediction error, which can theoreticallylead to more accurate demand algorithms [257]. Yetagain, industrial incentives must be aligned with reducingemissions.Recommender systems can potentially direct consumers and purchasing firms toward climate-friendlyoptions, as long as one can obtain information about GHG emissions throughout the entire life-cycle of someproduct. The challenge here lies in hunting down usable dataon every relevant material and productionprocess from metal ore extraction through production, shipping, and eventual use and disposal of a product[344, 345]. One must also convince companies to share proprietary data to help other firms learn from bestpractices. If these datasets can be acquired, ML algorithmscould hypothetically assist in identifying thecleanest options.Optimized supply chains, combined with improved heating and cooling systems [346] (see§4.3), canalso play a role in reducing food waste, which ranks as #3 on Project Drawdown’s list of climate changesolutions [18]. Globally, society loses or wastes 1.3 billion metrics tons of food each year, which translatestoone-thirdof all food produced for human consumption [347]. Developing countries lose 40% of this foodbetween harvest and processing or retail, while over 40% of food waste in industrialized nations occurs atthe end of supply chains, in retail outlets, restaurants, and consumers’ homes [347]. ML can help reducefood waste in all these contexts. The highest impacts will come from mitigating post-harvest losses throughoptimized delivery routes and more affordable climate control systems, as well as tackling retail and con-sumer losses through better demand forecasting at the pointof sale. ML can also potentially assist with otherissues related to food waste, such as helping develop sensors to identify when produce is about to spoil, soit can be sold quickly, or removed from a storage crate beforeit ruins the rest of the shipment [348].4.2 Materials and constructionHigh LeverageHigh RiskCement and steel production together account for approximately 9% of all global GHG emissions [132]; thecement industry alone emits more GHG than every country except the US and China [349]. Several studiesindicate that ML may be able to help minimize these emissionsby reducing the need for carbon-intensivematerials, by transforming industrial processes to run on low-carbon energy, or even by replacing cementand steel altogether with more efficient structural materials.To reduce the use of cement and steel, researchers have combined ML with generative design [330]to develop structural products that require less raw material, thus minimizing the resulting GHG emissions.Novel manufacturing techniques such as 3D printing allow for the production of unusual shapes that use lessmaterial but may be impossible to produce through traditional metal-casting or poured concrete; Baturynskaet al. used ML and finite element modeling to better simulate the physical processes of 3D printing in orderto improve the quality of finished products [350].Assuming future advances in materials science, ML researchers could potentially draw upon databasessuch as the Materials Project [351] to help invent new, climate-friendly materials with desirable chemicalproperties [352]. Researchers are also experimenting withsupervised learning and thermal imaging systemsto rapidly identify promising catalysts and chemical reactions [353, 354], as described in§1.1.1. Firmsare unlikely to adopt new materials or change existing practices without financial incentives, so widespreadadoption might require subsidies for low-carbon alternatives or penalties for high GHG emissions.4.3 Production and energyHigh LeverageML can potentially assist in reducing overall electricity consumption; streamlining factories’ heating, ven-tilation, and air conditioning (HVAC) systems; and redesigning some types of industrial processes to run onlow-carbon energy instead of coal, oil, or gas. Again, the higher the incentives for reducing carbon emis-25

sions, the more likely that firms will optimize for low-carbon energy use. New factory equipment can bevery expensive to purchase and set up, so many firms’ cost-benefit calculations may dissuade them fromretrofitting existing factories to run using low-carbon electricity or to save a few kilowatts [355–357].Ammonia production for fertilizer use relies upon natural gas to heat up and catalyze the reaction, andaccounts for around 2% of global energy consumption [358]. To develop cleaner ammonia, chemists maybe able to invent electrochemical strategies for lower-temperature ammonia production [358, 359]. Giventhe potential of ML for predicting chemical reactions [354], ML may also be able to help with the discoveryof new materials for electrocatalysts and/or proton conductors to facilitate ammonia production.On the production side, ML can potentially improve the efficiency of HVAC systems and other industrialcontrol mechanisms—given necessary data about all relevant processes. Deep neural networks could be usedfor adaptive control in a variety of industrial networking applications [360], enabling energy savings throughself-learning about devices’ surroundings. To reduce GHG emissions from HVAC systems, researcherssuggest combining optimization-based control algorithmswith ML techniques such as image recognition,regression trees, and time delay neural networks [361, 362](see also 3.1). DeepMind has used reinforcementlearning to optimize cooling centers for Google’s internalservers by predicting and optimizing thepowerusage effectiveness (PUE), thus lowering emissions and reducing cooling costs [331, 363].Air conditioning systems have an outsized impact on climate, as the hydrofluorocarbons (HFCs) theycontain are extremely potent greenhouse gases [364]; proper management of such refrigerants ranks #1on Project Drawdown’s solutions list [18, 365]. Computer vision and deep learning can potentially assistfactories and regulators in better detecting HFC leaks and improving disposal management, especially incombination with satellite imagery and data related to leak-prone equipment.ML could also contribute to predictive maintenance by more accurately modelling the wear and tear ofmachinery that is currently in use, and interpretable ML could assist factory owners in developing a betterunderstanding of how best to minimize GHG emissions for specific equipment and processes. For example,creating adigital twinmodel of some industrial equipment or process could enable amanufacturer to identifyand prevent undesirable scenarios, as well as virtually test out a new piece of code before uploading it tothe actual factory floor – thus potentially increasing the GHG efficiency of industrial processes [366, 367].Digital twins can also reduce production waste by identifying broken or about-to-break machines before theactual factory equipment starts producing damaged products. Industrial systems can employ similar modelsto predict which pipes are liable to spring leaks, in order tominimize the direct release of GHGs such asHFCs and natural gas.ML may be particularly useful for enabling more flexible operation of industrial electrical loads, throughoptimizing a firm’sdemand responseto electricity prices as addressed in§1. Such optimization can con-tribute to cutting GHG emissions as long as firms have a financial incentive to optimize for minimal emis-sions, maximal low-carbon energy, or minimum overall powerusage. Demand response optimization al-gorithms can help firms adjust the timing of energy-intensive processes such as cement crushing [332] andpowder-coating [368] to take advantage of electricity price fluctuations, although published work on thetopic has to date used relatively little ML. Online algorithms for optimizing demand response can reduceoverall power usage for computer servers by dynamically shifting the internet traffic load of data providersto underutilized servers, although most of this research, again, has focused on minimizing costs rather thanGHG emissions [72, 369]. Berral et al. proposed a framework that demonstrates how such optimizationalgorithms might be combined with RL, digitized controls, and feedback systems to enable the autonomouscontrol of industrial processes [333].4.4 DiscussionThere are a number of potentially useful applications for using ML to reduce GHG emissions in industry,although there has been little published research focused specifically on GHG reductions rather than cost26

savings. On the logistics side, ML may help optimize shipping routes and improving market demand pre-dictions in order to produce fewer unwanted goods. On the design and production side, the strategic use ofML can potentially reduce the need for GHG-intensive materials as well as optimizing industrial processesto use less energy and/or run on low-carbon fuels. Before applying ML to industry applications, however,researchers must consider questions such as the following:Who has access to the requisite data for train-ing? Under what circumstances does ML actually outperform regressions, naive forecasting algorithms, andother optimization solutions that require less data and maybe simpler to design and implement? Even ifML can improve some industrial system, can firms feasibly implement the solution? Will this improvementactually result in GHG mitigation, or are firms liable to respond with increased production and even greaterGHG emissions as indicated by the Jevons paradox?In conclusion, ML demonstrates considerable potential forreducing industrial GHG emissions underthe following circumstances:•When there are large amounts of accessible, high-quality data around specific processes or transportroutes.•When firms have an incentive to share their proprietary data and/or algorithms with researchers andother firms.•When aspects of production or shipping can be readily fine-tuned or adjusted, or when the benefits ofoverhauling old systems exceed the costs.•When firms’ incentives align with reducing emissions (for example, through efficiency gains, regula-tory compliance, or high GHG prices).Given the globalized nature of international trade and the urgency of climate change, decarbonizing theindustrial sector must become a key priority for both policy-makers and factory owners worldwide. If firmscan make more money by reducing their GHG emissions, market competition will drive companies towardscleaner and more efficient production and distribution – and, given the right datasets, ML researchers canhelp pave the way.

Adaptation7 Climate Predictionby Kelly KochanskiThe first global warming prediction was made in 1896, when Arrhenius estimated that burning fossil fuelscould eventually release enough CO2to warm the Earth by5◦C. The fundamental physics underlying Ar-rhenius’s calculations has not changed, but our predictions have become far more detailed and precise. Thepredominant predictive tools are climate models, known asgeneral circulation models (GCMs)orEarthsystem models (ESMs).45These models inform local and national government decisions (see IPCC reports[4, 26, 437]), help individuals calculate their climate risks (see§10) and allow us to estimate the potentialimpacts of solar geoengineering (see§9).Recent trends have created opportunities for ML to advance the art of climate prediction. First, new andcheaper satellites are creating petabytes of climate observation data.46Second, massive climate modelingprojects are generating petabytes of simulated climate data.47Third, climate forecasts are computationallyexpensive [441] (the simulations in [440] took three weeks to run on NCAR supercomputers), but MLapplications are driving the design of next-generation supercomputers that could ease current computationalbottlenecks. As a result, climate scientists have recentlybegun to explore ML techniques, and are startingto team up with computer scientists to build new and excitingapplications.7.1 Uniting data, ML, and climate scienceHigh LeverageClimate models represent our understanding of Earth and climate physics. We can learn about the Earth bycollecting data. To turn that data into useful predictions,we need to condense it into coherent, computation-ally tractable models. ML models are likely to be more accurate or less expensive than other models where:(1) there is plentiful data, but it is hard to model systems with traditional statistics, or (2) there are goodmodels, but they are too computationally expensive to use inproduction.When data is plentiful, climate scientists build many data-driven models. These models are mostly builtby solving regression and classification problems, and new ML techniques may solve many problems thatwere previously challenging. For example, the authors of [442–444] use ML to calibrate satellite sensors,classify crop cover, and identify pollutant sources. More applications like these are likely to appear as satel-lite databases grow. This year, Reichstein et al. proposed that deep learning could be used extensively forpattern recognition, super-resolution, and short-term forecasting in climate models [445], and Mukkavilliproposed to compile a new labelled dataset of environmentalimagery, called EnviroNet, that would accel-erate ML work in environmental science [446]. We recommend that modellers who seek to learn directlyfrom data see [447] for specific advice on fitting and over-fitting climate data.Many climate prediction problems are irremediably data-limited. No matter how many weather stationswe construct, how many field campaigns we run, or how many satellites we deploy, the Earth will generateat most one year of new climate data per year. Existing climate models deal with this limitation by relyingheavily on physical laws, such as thermodynamics. ML modelscan leverage existing physics-based modelsas data sources to solve important climate problems.Recent work has shown how deep neural networks and existing thermodynamics knowledge could becombined to fix the largest source of uncertainty in current climate models: clouds. Bright clouds blocksunlight and cool the Earth; dark clouds catch outgoing heatand keep the Earth warm [437, 448]. These45Learn the basics of climate modeling fromclimate.be/textbook[436] or Climate Literacy,youtu.be/XGi2a0tNjOo46e.g. NASA’s Earth Science Data Systems program,earthdata.nasa.gov, and ESA’s Earth Online,earth.esa.int47e.g. the Coupled Model Intercomparison Project,cmip.llnl.gov[438, 439] and Community Earth System Model LargeEnsemble [440]34

effects are controlled by small-scale processes such as cloud convection and atmospheric aerosols (see usesof aerosols for cloud seeding and solar geoengineering in§9). Physical models of these processes are fartoo computationally expensive to include in global climatemodels — but ML models are not. Gentine etal. trained a deep neural network to emulate the behavior of ahigh-resolution cloud simulation, and foundthat the network gave similar results for a fraction of the cost [449] and was stable in a simplified globalmodel [450]. Existing scientific models have fixed trade-offs between cost and accuracy, and sometimesthese trade-offs do not include any great solutions. Neuralnetworks trained on those scientific modelsproduce similar predictions, but offer an entirely new set of compromises between training cost, produc-tion cost, and accuracy. Replacing select climate model components with neural network approximatorsmay thus improve both the cost and the accuracy of global climate models. Additional work is needed tooptimize the cloud model above; to identify more climate model components that could be replaced by neu-ral networks (we highlight other impactful components below); to train neural networks that replace thosecomponents; and to build pipelines that re-train these neural networks in response to errors or extrapolation(example workflow in§4.5 of [442]).The next most important targets for climate model improvements are ice sheet dynamics and sea levelrise. The Arctic and Antarctic are warming faster than anywhere else on Earth, and their climates controlthe future of global sea level rise and many vulnerable ecosystems [4, 26]. Unfortunately, these regionsare dark and cold, and until recently they were difficult to observe. In the past few years, however, newsatellite campaigns have illuminated them with hundreds ofterabytes of data.48These data could makeit possible to use ML to solve some of the field’s biggest outstanding questions. In particular, models ofmass loss from the Antarctic ice-sheet are highly uncertain[451] and models of the extent of Antarctic seaice do not match reality well [452]. The most uncertain partsof these models, and thus the best targetsfor improvement, are snow reflectivity, sea ice reflectivity, ocean heat mixing and ice sheet grounding linemigration rates [447, 451, 453]. Computer scientists who wish to work in this area could build models thatlearn snow and sea ice properties from satellite data, or usenew video prediction techniques (e.g. [454]) topredict short-term changes in the extent of sea ice.ML could also improve climate model efficiency by identifying and leveraging relationships betweenclimate variables. For example, Nowack et al. demonstratedthat ozone concentrations could be computedas a function of temperature, rather than physical transport laws, which led to considerable computationalsavings [455]. Pattern recognition and feature extractiontechniques could allow us to identify more usefulconnections in the climate system, and regression models could allow us to quantify non-linear relationshipsbetween connected variables.In the further future, the Climate Modeling Alliance has proposed to build an entirely new climate modelthat learns continuously from data and from high-resolution simulations [456]. The proposed model wouldbe written in Julia, in contrast to existing models which aremostly written in C++ and inherited Fortran.At the cost of a daunting translation workload, they aim to build a model that is more accessible to newdevelopers and more compatible with ML libraries.Finally, the best climate predictions are synthesized fromensembles of 20+ climate models [457]. Mak-ing good ensemble predictions is an excellent ML problem. Monteleoni et al. proposed that online MLalgorithms (e.g. [458]) could select the best-performing model at any given point in time [459]; this idea hasbeen refined in further work [460, 461]. More recently, Anderson and Lucas used random forests to makehigh-resolution predictions from a mix of high- and low-resolution models, thereby reducing the costs ofbuilding multi-model ensembles [462]. These studies leaveroom for the development of more specializedand sophisticated ensemble methods. For example, climate models serve many users with different objec-tives. The model in [459] optimizes the ensemble to predict global temperature; however, their solution isnot necessarily optimal for users who need predictions of local temperatures, local rainfall, or the dates the48See e.g.icebridge.gsfc.nasa.govandpgc.umn.edu/data/arcticdem.35

Northwest Passage will open for shipping.7.2 Forecasting extreme eventsHigh LeverageFor most people, extreme event prediction means the local weather forecast and a few days’ warning tostockpile food, go home, and lock the shutters. Weather forecasts are shorter-term than climate forecasts,but they produce abundant data that makes them amenable to some ML techniques that would not workin climate models. Weather models are optimized to track therapid, chaotic changes of the atmosphere;since these changes are fast, tomorrow’s weather forecast is made and tested every day. Climate models, incontrast, are chaotic on short time scales, but their long-term trends are driven by slow, predictable changesof ocean, land, and ice (see [463]).49As a result, climate model output can only be tested against long-term observations (at the scale of years to decades). Intermediate time scales, of weeks to months, areexceptionally difficult to predict, although Cohen et al. [464] argue that machine learning could bridge thatgap by making good predictions on four to six week timescales[465]. Thus far, however, weather modelershave had hundreds of times more test data than climate modelers, and began to adopt ML techniques earlier.Numerous ML weather models are already running in production. For example, Gagne et al. recently usedan ensemble of random forests to improve hail predictions within a major weather model [466].Climate models do predict changes in long-term trends like drought frequency and storm intensity,although they cannot predict the specific dates of future events. These trends help individuals, corporationsand towns to make informed decisions about infrastructure,asset valuation and disaster response plans (seealso§8.4). Identifying extreme events in climate model output, however, is a classification problem witha twist: all of the available data sets are strongly skewed because extreme events are, by definition, rare.ML has been used successfully to classify some extreme weather events. Liu et al. used deep convolutionalneural networks to count cyclones and weather fronts in climate data sets [467], and Lakshmanan has deviseda series of techniques to track storms and tornadoes (e.g. [468]). Tools for more event types would be useful,as would online tools that work within climate models, and statistical tools that quantify the uncertainty innew extreme event forecasts.Forecasts are most actionable if they are specific and local.ML is widely used to make local forecastsfrom coarse 10–100 km climate or weather model predictions;various authors have attempted this usingsupport vector machines, autoencoders, Bayesian deep learning, and super-resolution convolutional neuralnetworks (e.g. [469]). Several groups are now working to translate high-resolution climate forecasts intorisk scenarios. For example, ML can predict localized flooding patterns from past data [470], which couldinform individuals buying insurance or homes. Currently, flood maps from the U.S. Federal EmergencyManagement Agency (FEMA) (part of the National Flood Insurance Program) do not account for the effectsof climate change on flooding [471]. Since ML methods like neural networks are effective at predictinglocal flooding during extreme weather events [472], these could be used to update local flood risk estimatesto benefit individuals. The start-up Jupiter Intelligence50is working to make climate predictions moreaccessible and actionable to companies and local governments, by translating climate forecasts into localisedflood and temperature risk scores.A full review of the applications of ML for extreme weather forecasting is beyond the scope of thisarticle. Fortunately, that review has already been written: see [473]. The authors describe ML systems thatcorrect bias, recognize patterns, and predict storms. Moving forward, they envision human experts workingin sync with automated forecasts.49This is one of several reasons why climate models produce accurate long-term predictions in spite of the chaotic nature of theatmosphere.50https://jupiterintel.com/36

7.3 DiscussionML may change the way that scientific modeling is done. The examples above have shown that manycomponents of large climate models can be replaced with ML models at lower computational costs. From anML standpoint, learning from an existing model has many advantages: modelers can generate new trainingand test data on-demand, and the new ML model inherits some community trust from the old one. This is anarea of active ML research. Recent papers have explored data-efficient techniques for learning dynamicalsystems [474], including physics-informed neural networks [475] and neural ordinary differential equations[128]. In the further future, researchers are developing MLsolutions for a wide range of scientific modelingchallenges, including crash prediction [476], adaptive numerical meshing [477], uncertainty quantification[478, 479] and performance optimization [480]. If these solutions are effective, they may solve some of thelargest structural challenges facing current climate models.New ML models for climate will be most successful if they are closely integrated into existing scientificmodels. This has been emphasized, again and again, by authors who have laid future paths for artificialintelligence within climate science [450, 456, 473, 481]. New models need to leverage existing knowledgeto make good predictions with limited data. In ten years, we will have more satellite data, more interpretableML techniques, hopefully more trust from the scientific community, and possibly a new climate modelwritten in Julia. For now, however, ML models must be creatively designed to work within existing climatemodels. The best of these models are likely to be built by close-knit teams including both climate andcomputational scientists.