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Artificial Intelligence for Agriculture

University of Maine Artificial Intelligence Initiative

UMaine Artificial Intelligence: AI for Agriculture

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UMaine AI draws top talent and leverages a distinctive set of capabilities from the University of Maine and other collaborating institutions from across Maine and beyond, while it also recruits world-class talent from across the nation and the world. It is centered at the University of Maine, leveraging the university's strengths across disciplines, including computing and information sciences, engineering, health and life sciences, business, education, social sciences, and more.

Transcript is machine generated, unedited, in English.

00:00
so welcome to the university of maine's
00:03
artificial intelligence webinar series
00:05
today's panel is focused on ai for
00:08
agriculture
00:09
um before we start i'd like to thank the
00:11
university of maine's office of the vice
00:12
president for research for planning this
00:14
event
00:15
and ieee main communication and computer
00:18
societies
00:19
joint chapter for sponsoring this
00:20
webinar
00:22
before we begin i want to remind those
00:24

of you attending to use the q
00:26
a feature to post your questions all
00:28
these questions will be asked
00:30
after each of the speakers or after all
00:32
of the speakers have completed their
00:33
presentations
00:35
so again thank you for joining us and it
00:37
is now my great pleasure to introduce
00:38
our first panelists
00:41
today we have joining us dr stephen j
00:44
thompson
00:44
he is the national program leader with
00:47
the usda national institute for food and
00:49
agriculture
00:50
he engages universities other federal
00:52
agencies and industry
00:54
to provide national leadership in
00:56
capacity and competitive grant programs
00:59
so with that i'd like to introduce steve
01:01
thank you
01:02
yes i'm stephen thompson um with uh
01:06
usca nifa i've been with nifa about
01:09
a little over five years now and
01:13
the national program leader in the uh
01:15

agriculture systems division i'm an
01:17
engineer by
01:18
training had
01:22
my background i was on faculty in two
01:25
different departments at virginia tech
01:28
and i was with usdar at usda
01:31
ars before i came here
01:34
so um it was associate professor
01:37
at virginia tech in the 90s so anyway
01:41
so let me give you a quick update first
01:44
on
01:44
uh some changes that have been made uh
01:47
secretary of the new secretary of
01:48
agriculture
01:49
tom vilsack he's been here before he
01:52
served under president obama
01:54
and we expect continuing interest in
01:57
some of the initiatives that are already
01:59
there
02:00
rural broadband precision ag he was a
02:03
big
02:04
proponent of robotics um in agriculture
02:08
and uh climate smart agriculture will be
02:12
more pronounced in this administration
02:15

dr
02:15
carey castille she was a science advisor
02:20
to the commissioner
02:21
for the louisiana department of
02:23
agriculture and forestry
02:25
she has an extensive extension
02:27
background
02:28
so i'll give you a short outline this
02:30
first part of the presentation
02:32
will not take very long i'm just going
02:34
to
02:36
emphasize a couple of aspects in plant
02:38
agriculture and
02:40
an example for a precision livestock
02:43
farming
02:44
and then i will get into the stuff you
02:47
really want to see
02:50
programs that involve some of most of
02:52
the research programs and the technical
02:54
side of things
02:55
that involve ai and usda nifa i'm not
02:58
going to talk about the educational
03:00
programs
03:01
but there are some uh you can
03:04

uh you can actually see those in the um
03:08
online on the nifa website
03:11
time won't allow me to get into the
03:13
weeds on every program
03:15
and then some future future outlook so
03:19
i want to center on one aspect of ai
03:22
cyber physical systems which
03:26
basically is pretty broad terms where
03:29
where physical and software components
03:31
are deeply intertwined
03:32
and they operate at different spatial
03:35
and temporal scales
03:36
and so you know many times you'll you'll
03:39
be
03:40
you'll have a system with sensing um
03:44
interpretive um should i say adaptive
03:47
control
03:48
data analytics in the middle part and
03:50
then an output control
03:52
or decision and there are feedback
03:55
loops involved you may have modeling
03:59
in working in concert with sensing these
04:02
kinds of things
04:05
um you know some of the obstacles
04:08

for i would say tech adoption and
04:11
cps the reason i say this is because
04:13
that middle part
04:14
is so important you know you have the
04:16
sensing but then the interpretation
04:19
how how ultimately how the
04:23
farm manager is going to be able to use
04:25
this is extremely important
04:28
there's some issues on the perceived
04:30
relevance of the technologies
04:32
actually just awareness of the available
04:34
technologies has been a
04:36
problem farmers like to fix things so
04:39
simplicity users guides this is not only
04:43
good for the farmer but for any
04:44
consultant that
04:45
is working with the farmer and and
04:48
there's been an issue with trust in tech
04:50
and dss
04:51
decision support recommendations now one
04:53
of our speakers um
04:56
later is going to talk about the
04:57
adoption side
04:59
and you know in a lot yeah i think
05:03

he has a very creative um he's going to
05:06
talk about a very
05:07
creative solution to this kind of shall
05:10
i say towards a solution to this kind of
05:11
thing so i will not
05:13
talk too much about the adoption area
05:16
now when you're talking about
05:18
uh plant-based management
05:24
you know there there are a lot of
05:26
sensors out there
05:28
they could be ground sensors aerial
05:31
sensors various things
05:32
and there are varying opinions on which
05:34
sensing systems work better
05:36
to detect certain anomalies in the field
05:39
okay but that research
05:40
is progressing and has progressed well
05:44
the like i say said before the middle
05:47
part of it the interpretive
05:50
kicker right part uh let me give you a
05:54
very short history on the precision ag
05:57
side of things back in the
05:59
mid 80s people were starting to realize
06:04
that
06:06

know you could you could have a cis
06:09
a setup where you're applying
06:13
inputs only to where they are needed
06:15
okay
06:16
and an article from 1985 that you won't
06:19
you won't find um i have a printed copy
06:23
but
06:23
it's i could not find it anywhere else
06:26
um farming by the foot proposed use
06:31
of lauren c technologies
06:34
uh which you know the uh accuracy is not
06:38
nearly as good as gps
06:41
but this was a concept in the early 80s
06:43
john schuler at the university of
06:45
florida
06:47
developed a combine yield map in 1986
06:51
i think this was this was a manually
06:54
obtained data
06:56
so this gives you an idea where the uh
06:59
when these concepts were first
07:01
thought about some work from my own
07:05
um background this was about a little
07:07
over 20 years ago
07:09
we thought hey you know let's just take
07:11

a high-res
07:13
video camera and put it in a
07:16
crop duster so anyway
07:20
we got an image like this and we were
07:23
able to
07:24
separate out we
07:28
grass weeds from broadleaf weeds and
07:31
cotton just as a conceptual idea
07:34
for future use in targeted spraying
07:39
for example this is
07:42
graduated to much more sophisticated
07:45
systems
07:46
up on the top left is a push broom
07:49
hyperspectral scanner
07:50
on uas these scanners have
07:54
decreased in size one on the top right
07:58
is a hyperspectral scanner that is a
08:01
frame based system of these companies in
08:05
finland
08:07
there are some companies in finland that
08:09
have developed these frame based systems
08:12
which are uh
08:13
would be easier to use but i don't have
08:15
any experience with them so
08:17

i'd be very interested to know one on
08:20
the bottom
08:21
is called a red edge um a
08:26
multi-spectral imaging system by a
08:28
company called micro
08:29
mica sense and um
08:34
so they're just they're basically
08:36
filters in
08:37
certain ranges of the optical spectrum
08:41
including near-infrared
08:44
also and
08:48
i alluded to this before cyber fiscal
08:50
systems can be the bridge in my opinion
08:53
i think
08:54
these will work better if you have sensi
08:58
if you have sensing and modeling or
09:01
sensor fusion sensing and modeling and
09:02
synergy
09:04
um i mentioned that the data analytics
09:06
part
09:07
it's very important to get that right
09:10
dss tools decision support tools are
09:14
readily
09:14
or becoming readily available for some
09:16

applications but not
09:18
others i've actually uh
09:22
funded a couple of grants for irrigation
09:24
for example where one is coming out
09:26
trying to reduce all these decisions
09:29
into a usable app
09:30
for the farmer so we'll see how that
09:32
goes
09:35
now i just want to point out
09:39
the bottom part here we're talking about
09:42
um
09:42
data interpretation and adoption
09:46
i would say now this is a slide dealing
09:49
with
09:50
variable rate technologies but this can
09:52
apply to many different
09:54
aspects say the low adoption on inputs
09:58
that require more data analysis of
10:00
prescription
10:02
algorithm development and this has been
10:04
the case this is from
10:05
a this is part of a slide from a study
10:09
on adoption from purdue university
10:13
so um i want to give one example
10:19

irrigation example look at the
10:22
yellow no not the blue and
10:26
green bars there
10:29
adoption of technologies for for
10:32
irrigation has been
10:34
really really poor very poor so
10:38
let's conceptualize something you may
10:40
have
10:41
some this is not really a flow chart but
10:43
there is flow here
10:44
you may have sensors in the field you
10:46
may have a
10:49
model of water balance that also depends
10:52
on
10:53
root distribution and root water uptake
10:56
in different zones
10:58
so in a nutshell what this one is doing
11:01
is using sensing and modeling and
11:04
synergy to make better estimates
11:08
okay so this is kind of this is a cyber
11:10
physical system in a way
11:15
let's not forget technology for small
11:18
farms
11:19
now this is something i was involved
11:21

with you can't get any simpler than this
11:24
this is a wash
11:25
tub with a toilet float and two marks on
11:28
the
11:28
back plate the the black mark would say
11:32
ear uh field capacity
11:35
uh that means well watered conditions
11:38
the red line would say irrigate
11:42
the trick is calibrating this to the
11:44
crop
11:45
soil combination and in my study i also
11:49
used soil water sensors in synergy with
11:53
this
11:54
so so we did publish something
11:57
on on use of this evaporation pan
12:01
and then in the future what you would do
12:03
is try to translate this into something
12:06
uh you you might actually take a signal
12:09
from this wash tub and send it remotely
12:11
or something
12:12
if you wanted to do that this is a very
12:15
simple concept
12:16
and not just for small farms it can be
12:18
used for big larger farms also
12:20

farmers like simple okay but there's a
12:23
lot more to
12:24
calibrating this than meets the eye
12:27
microsoft has actually gotten into the
12:29
game too
12:31
where they are essentially replacing
12:34
expensive ground
12:35
place sensors with cheap wi-fi receivers
12:39
at several locations and the principle
12:42
here is to measure the relative
12:44
time of flight of a signal to infer uh
12:47
soil properties and this is very good
12:50
paper at the bottom i would uh
12:52
suggest you get hold of this is just a
12:55
proceedings article
12:57
but uh for a proceedings
13:00
article the the results look very very
13:04
promising
13:06
livestock farming what you're doing here
13:09
is you have
13:12
to make immediate decisions in real time
13:16
whereas plant-based for plant-based um
13:19
agriculture you can
13:22
uh make decision in near real time and
13:25

depending on what you're looking at
13:27
and many times you're saving the data
13:29
from year to year say
13:31
if you have yield maps
13:34
you want to know what the yield trends
13:36
are from year to year
13:38
okay in this case
13:41
you have to take uh for animal comfort
13:43
and these kinds of things
13:45
many sensing inputs like biosensing
13:48
environmental
13:49
uh diagnostics of the systems is a is a
13:53
big
13:53
part of precision livestock farming
13:56
that's what plf
13:57
stands for and you have some of the
14:00
same concepts as you do for plant
14:04
plant-based you'll have sensing you may
14:06
have modeling
14:07
adaptive learning and i would also
14:10
submit that visual monitoring is a big
14:12
part of this too
14:13
you know i can envision having a large
14:15
screen with many many bar graphs so
14:18

the farm manager not only you know
14:22
this model based analysis uh could be
14:25
black boxed but if the farm
14:27
farm manager sees uh
14:30
sees the data up on the screen they may
14:33
actually look at some hey this doesn't
14:35
look right you know and
14:36
and uh check check out what's going on
14:39
and this could also be used to
14:41
uh update the algorithms you know in a
14:44
system like this so this is just a
14:46
concept
14:47
okay uh if i'm not short on time
14:51
i'm going to get through this
14:54
i want to mention how nifa funds are
14:56
provided let's get to the grant side
14:58
about 50 percent of our funding goes to
15:01
capacity grants
15:02
50 to competitive grants the capacity
15:06
would be
15:07
the hatch uh evans allen mcintyre
15:10
sentence and these type and i would
15:12
implore people to
15:14
you know when you're sending a um
15:16

project initiation for a capacity grant
15:19
really pay attention to the detail on
15:20
this
15:21
as uh you know if you see if i see a
15:25
three sentence methods i'll send it back
15:26
so make sure
15:27
these are fleshed out very nicely all
15:30
right
15:31
i'm going to go down the list here and
15:33
uh some with more detail than others
15:36
the first one is an engineering for
15:38
agricultural production systems now this
15:40
is in the afri
15:42
um portfolio
15:45
the funding the funding amount has gone
15:48
up to 650k
15:50
per grant
15:55
the funding rate's been rather low
15:56
though i had a
15:58
40 increase in the number of proposals
16:02
from 2019 to 2020.
16:06
funding rates down near 9 with the same
16:08
amount of money
16:10
data science for ag systems funding
16:12

rates a little bit higher
16:14
the 1 million level is for uh
16:18
cins which is uh
16:21
coordinated innovation networks okay
16:25
national robotics initiative is
16:28
now for these you need to look at the
16:30
nsf website to see the solicitations
16:34
however national robotics initiative
16:37
cyber physical systems these are both
16:40
funded by nifa and the panels are run by
16:43
nsf
16:44
uh nifa has a say in helping select the
16:47
panelists on this also
16:50
most of the all of the nifa submissions
16:52
have been
16:53
within the near within the real-time
16:56
agricultural data analytics and control
17:00
section smart and connected communities
17:03
is also a part of this
17:04
and you can see what our memphis aspect
17:08
is on that
17:10
signals in the soil another one uh
17:13
jim dombrowalski has
17:16
five million dollars my contribution is
17:19

variable
17:20
according to the budget a few more
17:24
pertinent programs
17:25
ai institutes of course these are the
17:28
big ones
17:28
we are in the process of reviewing
17:32
proposals now for the second year of
17:34
funding we funded two grants for 2020
17:37
one from uh pi from davis california the
17:41
other
17:41
university of illinois and several
17:43
several collaborators
17:45
collaborative universities and companies
17:47
too
17:48
um we're working on the solicitation for
17:52
2022
17:54
we will fund at least one grant out of
17:57
that one
17:58
sbir of course plant production and
18:01
protection engineering program
18:02
is one out of 10 programs from our
18:06
sbir portfolio there's a 15
18:09
funding rate across the board if you are
18:12
registered in sam you have to be
18:14

registered in sam's and have a duns
18:16
number or you won't get through the
18:17
front door
18:18
small and medium farms there are some
18:21
pretty interesting technology-based
18:24
uh technology-based grants funded out of
18:27
that program also
18:30
now if you're involved in the adoption
18:32
or diffusion of agricultural
18:34
technologies
18:35
one of these three programs should be
18:37
considered
18:38
especially economics markets and trade
18:42
okay so that one we're actually
18:43
modifying to enhance
18:45
uh these aspects
18:48
yes i think we're over a bit if you want
18:51
to just
18:52
put up your final yeah this is my final
18:55
slide
18:56
thank you a couple of observations we
18:59
need to integrate
19:00
social sciences even more in our grant
19:02
programs
19:03

um and emphasize extension and education
19:07
more
19:08
in aai institutes anyway you can read
19:12
all this
19:12
i'm over time so we'll talk about it
19:15
later
19:16
thank you very much
19:19
and uh if you have uh if you want to
19:22
serve on a grant panel send me a cv
19:25
to find grant summaries look uh google
19:27
usd
19:28
cris and use the assisted search thank
19:30
you very much
19:32
thank you so much very very well done
19:36
so for our next speaker i'd like to
19:39
introduce
19:39
dr nuresh davanini he is an associate
19:43
professor in the department of civil
19:44
engineering
19:45
at the city university of new york city
19:46
college he holds an ms and phd in civil
19:49
engineering from north carolina state
19:51
and he did his post-doctoral studies at
19:53
columbia so with that
19:54

uh thank you dr davanini great
19:58
thanks susan i'm gonna share my screen
20:01
so today the title for this talk is
20:04
the role of big data analytics in
20:06
securing the future of water
20:08
energy and food really what i'm trying
20:10
to present here is
20:12
the applications of the classical ai
20:15
techniques like process optimization
20:17
predictive models and how we can use big
20:20
data
20:20
to how we can leverage big data and use
20:23
these classical ai techniques
20:25
to find solutions for water food energy
20:28
problems that we are
20:29
seeing a lot these days so on that i'm
20:32
going to present two stories
20:34
one is an application in india and one
20:36
is an application in the us
20:38
both problems are national at scope for
20:41
the case of india the problem
20:42
identification is that
20:44
there is an unsustainable practice
20:46
agricultural practice currently going on
20:48

in india
20:49
that will lead to an acute water stress
20:51
it is already water stress but it will
20:52
really
20:53
lead to much more acute stress if the
20:55
practices are continuing
20:56
so for identifying this problem much
20:59
more closely what we did is to
21:01
use big data from disparate sources we
21:03
assimilated all of those things
21:05
and we tried to learn about the current
21:07
water stress using the big data so we're
21:08
learning about water stress from the
21:10
data
21:10
and then the solution we propose is then
21:13
to use data-driven predictive techniques
21:15
and process optimization these are like
21:17
the classical systems methods
21:19
to remove the stress while still
21:20
achieving food security in india
21:22
so in a way we're trying to find can we
21:24
really solve this problem using ai
21:26
techniques
21:27
in the second application which is the
21:29

planning for united states agriculture
21:31
for climate change
21:32
the problem identification is that
21:33
extreme temperatures under climate
21:35
change
21:36
will reduce yields for several of the
21:38
major u.s crops
21:39
so for that we try to use a bayesian
21:41
learning method to understand and
21:43
predict
21:44
crop yields based on technology based on
21:46
temperature and water stresses
21:48
and the solution we're trying to come up
21:50
with is use again systems optimization
21:52
methods
21:53
to predict crop switching strategies to
21:55
mitigate yield losses
21:57
so i'll start with the first story which
21:58
is the story of india and here i'd like
22:00
to acknowledge my
22:02
colleagues here umanullah from columbia
22:04
university and sharma parveen
22:06
here the question is based on the
22:08
current crisis in india
22:10

can can we solve this issue and make
22:12
india one of the
22:13
leading agricultural sustainable
22:15
producers
22:16
in the market with an end times boost in
22:18
the rural income
22:20
but really let's look at the problem
22:22
first if you look at this
22:24
these two images one is an image on the
22:26
left which is
22:27
uh provided by gray satellite which was
22:29
detecting largest groundwater mining
22:31
operations in the world
22:33
and that region that you see here which
22:35
is in red color
22:36
is also the place like the football of
22:39
india it is heavily populated and what
22:41
you're seeing on the right is
22:43
uh the actual groundwater extractions
22:45
the number of wells
22:46
that are installed in those places as
22:48
you can see like heavily populated
22:50
region
22:50
uh heavy groundwater extractions mainly
22:53

for the purpose of
22:54
agriculture but this problem has
22:57
actually started in the 1950s and 60s
23:00
when the country went through a big
23:01
famine
23:01
and food insecurity because of low
23:03
yields and high fluctuation
23:05
poor storage distribution system there
23:07
were market fluctuations
23:09
there was stock manipulation to arrest
23:11
the trend what the government has done
23:13
at that time is to float this idea
23:15
called the national grain
23:16
procurement stream where there was
23:18
guaranteed price on
23:20
select crops and all these crops used to
23:22
be procured for
23:23
the purpose of national food security so
23:26
this really initiated the green
23:27
revolution
23:28
where you have improved cultivators
23:30
better fertilizers and practices
23:32
there were research and extension
23:34
programs created by the government
23:36

while at the same time it was also
23:37
giving irrigation provisions to buffer
23:39
climate variability
23:40
and one of the biggest uh additions at
23:43
that time was to give electricity and
23:45
water for free
23:46
which means that we have heavy
23:48
groundwater installations and as a
23:50
result we have huge groundwater pumping
23:52
to sustain the climate variability for
23:54
agriculture the figures on the right
23:56
that you see here is that
23:58
just to outline that india is one of the
24:01
highest grown water extractors
24:03
compared to a lot of countries in the
24:04
world and the figure on the bottom you
24:06
see here is that
24:07
although india has other sources of
24:09
irrigation like canals and tanks
24:11
because of their unreliability and
24:13
because of
24:14
guaranteed prices and free electricity
24:17
the trend of usage of groundwater
24:18
irrigation has gone up
24:20

significantly so it's now one of the
24:21
predominant agriculture irrigation
24:23
technologies india is just extracting
24:25
groundwater
24:27
and as a result what you can see here is
24:29
this is the current cropping pattern
24:31
a lot of the cropping patterns have
24:33
shifted from their traditional practices
24:35
which used to be their done before the
24:37
1950s now because
24:39
their farmers are reacting to these
24:40
incentives what you see here is
24:42
rice has moved to the northwest
24:45
countries
24:46
of punjab states of punjab and haryana
24:48
and uttar pradesh
24:50
and what used to be pulses and cereals
24:53
are now completely not grown in that
24:55
place
24:55
but when you look at the climate side of
24:57
the story you find that that place where
24:59
you are actually growing rice currently
25:01
is uh is a dry land and this is a place
25:04
where you only get a third of what is
25:06

required by rice
25:08
but nevertheless this place contributes
25:10
to the highest grain production in the
25:11
country
25:12
because most of that is coming from the
25:14
irrigation
25:15
which is coming from groundwater and as
25:17
a result you see that
25:18
while you have food security now you are
25:21
coming it's coming at a risk of water
25:23
security for the future of the country
25:26
so the first thing we did was to
25:28
identify what this stress is so we're
25:30
trying to use this big data methods to
25:32
identify the stress predict the water
25:34
stress in the country and look at what
25:36
are these
25:36
stressy zones so for this what we did
25:39
was assimilate a large database
25:41
a hundred years worth of daily climate
25:43
rainfall temperature data
25:45
we assimilated all the current cropping
25:47
data sets from india at the district
25:49
level
25:49

and you can see the dimensionality is
25:51
really like multi multiple-fold
25:53
the data sources can come from various
25:55
sources a lot of them from government
25:57
websites
25:58
a good number of them from research
26:00
articles and just talking to locals and
26:02
getting those surveys we used all the
26:05
data to first predict
26:06
water stress measured which is really a
26:08
function of rainfall temperature
26:10
evaporation water demands and crop
26:12
biophysical characteristics
26:14
and what you see here is just an
26:15
illustration of that water stress
26:17
without going into much detail what you
26:20
can see is that if it is in the red zone
26:22
it is really bad
26:24
both at the annual water stress measure
26:26
and
26:27
when you look at multi-annual it is also
26:28
very bad meaning if this place is
26:30
susceptible to multiple years of drought
26:32
the stress really accumulates and
26:34

becomes a chronic problem in stock just
26:36
an annual problem
26:37
and when we integrate these two annual
26:38
and multi-annual stressors what you'll
26:40
see here are
26:41
a development of uh an agroecological
26:44
zone sort of what we are seeing here is
26:46
that
26:46
some places are sustainable which are
26:48
the blue zones some places are prone to
26:50
multiple years of stress multiple years
26:52
of drought
26:52
which are the red zones and some places
26:54
are really unsustainable for agriculture
26:57
at least based on the current cropping
26:58
pattern so the green zones that you see
27:00
here
27:00
which means that you really need
27:01
shifting of crops from those places
27:04
so then if this is a problem what the
27:06
solution we're trying to propose is
27:08
can we actually use all this big data in
27:10
a systems method
27:12
uh process optimization is what it's
27:14

called in ai language
27:15
to predict what the sustainable zones of
27:17
agricultural enhancement would be
27:19
so that way we're trying to address
27:20
climate energy water
27:22
food income nexus all conjunctively in
27:24
one solution
27:26
and the question we started asking was
27:28
when we looked at this figure which is
27:30
the acreage of rice and pulses in punjab
27:34
the northwest part of india
27:36
you can see since the 1970s there's a
27:38
huge increase in the cultivation of rice
27:40
and a huge drop in the cultivation of
27:42
pulses which used to be the traditional
27:44
crops in those places
27:45
and much of this rice as i said it's not
27:47
it's not raining so much there
27:49
but all that irrigation is coming from
27:51
groundwater and you know in fact
27:52
up to 70 or 80 percent of that
27:54
irrigation is really for groundwater
27:56
so we started asking this question like
27:58
can we use some
27:59

data analytic techniques to solve this
28:01
so the question is did the green
28:03
revolution really stick in the wrong
28:04
places
28:05
could india's water stress be reduced
28:07
just by changing where
28:09
what is grown so then can these analytic
28:12
methods help us identify what those
28:14
zones are
28:15
and how much to grow in those places
28:17
like a decision tool and
28:18
what is the role of climate in these
28:20
things so we created this large scale
28:23
process optimization model
28:24
which is trying to predict sustainable
28:26
zones for agricultural enhancement
28:28
the inputs of this model are the climate
28:30
scenarios more than 100 years of climate
28:33
precip and temperature at the district
28:35
level and the crop eligibility whether
28:37
the crop can be grown there or not
28:39
we are using all those inputs to predict
28:41
water stress
28:42
which will predict crop yields which
28:44

will in turn predict crop production
28:46
then the other inputs are current prices
28:48
of the crops
28:49
cost of cultivation cost of irrigation
28:51
so all those go into this process
28:53
optimization and the objective is to
28:55
maximize the national revenue that is
28:57
coming from agriculture
28:58
while we have a bunch of constraints
29:00
which are trying to keep the things
29:02
sustainable
29:02
we don't want to increase the land which
29:04
is currently under
29:06
agriculture meaning we are already maxed
29:08
out on land so we are not using more
29:10
land
29:10
and we are trying to keep irrigation to
29:12
a sustainable limit
29:13
and we also played around with a
29:15
scenario where there is no irrigation at
29:16
all across the country
29:18
and you'd be surprised that even without
29:19
irrigation you can still get national
29:21
food security
29:22

on an average year so the model runs as
29:25
a
29:26
simulation optimization model uh and you
29:29
can develop multiple scenarios out of
29:31
these things and identify what are these
29:32
best zones
29:33
so before looking at the results i'll
29:35
show you this plot again
29:36
that this is the current cropping
29:39
practice where you have
29:40
a lot of crop of rice in that northwest
29:43
part
29:44
and the other cereals which used to be
29:45
the traditional crops were not
29:47
are not there currently now when you run
29:49
this model and identify what are the
29:51
solutions that come from this model
29:53
you'll find that in the northwest part
29:55
of india the rice is completely removed
29:58
and it's been replaced by other cereals
30:00
both under the green water scenario in
30:02
the blue water scenario which is
30:04
you know assuming there is no irrigation
30:05
in the entire country completely green
30:07

and assuming there is some sustainable
30:09
irrigation which is
30:10
renewed on an annual basis that is the
30:12
blue water scenario
30:14
you can see uh there's a 75 reduction in
30:16
how much crop goes into those places
30:18
and it's been replaced by traditional
30:20
crops that used to be grown there
30:22
now when you look at at the national
30:24
level how much revenue you can generate
30:26
uh it is much greater at least thirty
30:28
percent greater than the current revenue
30:30
that you can generate
30:31
this is the sustainable irrigation
30:33
scenario even the rain fed scenario is
30:35
five percent
30:36
greater than what you're currently
30:37
generating all the other production
30:39
limits
30:40
are met or even we are producing more
30:41
than what we need for now
30:43
uh this also calls for the story that
30:45
currently the country imports a lot of
30:47
oil seeds and pulses but with this
30:49

optimized scenario
30:50
you can look at reducing those
30:52
dependencies on external trades also so
30:55
if the country becomes completely
30:56
self-sustained
30:57
for all the types of crops that you need
30:59
and an even bigger opportunity here
31:01
is that if the corporations and
31:03
government participate together
31:05
to address market risks and price risks
31:08
and also provide help in terms of
31:09
technology innovations in the
31:11
agriculture supply chain
31:12
the story is even bigger because you're
31:14
really solving a national problem
31:16
using a well-established ai technique
31:20
uh in the next story what i'm going to
31:22
present is how do we plan
31:25
united states agriculture for climate
31:26
change and i'd like to acknowledge my
31:28
colleague here from london school of
31:30
economics james rising
31:33
so here the problem was extreme
31:35
temperatures in the u.s under climate
31:37

change will reduce yields for several of
31:39
the major crops
31:40
so the first thing we try to identify
31:42
here is a learning technique a bayesian
31:44
learning technique to understand and
31:45
predict
31:46
crop yields based on technology
31:48
temperature and water stresses and the
31:49
solution we proposed are
31:51
using systems methods to predict props
31:54
switching strategies
31:56
very quickly without taking much time
31:58
i'll the it has two
31:59
aspects to it the first part is a
32:02
complete
32:02
uh yield prediction model that is trying
32:05
to predict yields for every county for
32:07
the
32:08
past 50 60 years using climate inputs
32:10
and water stress inputs
32:12
then it's a learning model so it right
32:14
tries to understand what is the
32:16
influence of temperature on each of
32:17
these crop yield
32:18

parameters then the second level is use
32:21
all these things all the predicted
32:22
yields
32:23
with an economic optimization for
32:25
decision analytics for future climate
32:27
this is akin to the optimization
32:29
technique so a
32:31
quick example of how a yield prediction
32:33
model looks like
32:34
the red color line is there two two
32:35
examples from two counties here
32:37
the model predicted yields are presented
32:39
in the black box plots the distributions
32:42
and the red color line is the observed
32:44
yield so you can clearly pick up the
32:45
technology trend
32:46
you can pick up the variability also
32:48
across the years based on the climate
32:50
stressors that it's being applied on
32:52
and finally we did the optimization
32:56
model we looked at what are the best
32:57
locations for 2050 and 2070 under future
33:00
climate scenarios
33:01
and you find that corn slowly becomes
33:03

less concentrated in the midwest
33:05
soybeans show gradual movement to the
33:07
north winter wheat moves up from the
33:09
south
33:10
along the mississippi cotton is grown at
33:12
higher latitudes compared to now
33:14
and it becomes it become dominant in the
33:16
future in the southern california area
33:18
when you look at the overall revenue
33:20
that the country can generate purely
33:22
from agriculture from these crops
33:24
you can see that the optimized scenarios
33:25
are always better than the current
33:27
observed scenarios
33:28
under future climate 2050 2070 scenarios
33:32
you do have reduction in the revenue but
33:34
then the optimized scenarios are much
33:36
better than
33:37
if you actually continue to grow where
33:39
you're growing today because
33:40
the future climate is going to reduce
33:42
the yields that means some locations are
33:43
not going to be
33:44
optimal anymore so we try to find the
33:46

optimal solutions using decision
33:48
analytics
33:50
finally i would like to close with
33:51
saying that there are multiple
33:53
possibilities with ai
33:55
to solve the multi-scale agricultural
33:57
issues so the solutions
33:58
can be applied at multiple scales and at
34:00
every scale you have possibilities with
34:02
ai
34:03
starting with at the national level if
34:05
you want to optimize where what is grown
34:07
you have analytics type of models to
34:08
develop those things
34:10
again at the national level the it's
34:12
mainly driven by economic signals
34:14
and storage and management signals those
34:17
also
34:17
can be left we can use big data to
34:19
leverage those ideas and try to give
34:21
better pricing forecasts
34:23
better climate forecasts better market
34:25
forecasts so that we
34:26
adapt to that future conditions and on
34:29

the farm technologies which is like at
34:31
the local scale
34:32
we can have efficiency in irrigation
34:34
monitoring and practices
34:36
uh rainfall crop productivity can be
34:38
increased by on-form technologies
34:40
you can have better soil sensing also
34:43
using all these like
34:44
robotic technologies and things for the
34:46
long term you can also develop
34:48
uh his traditional risk management
34:51
models
34:51
which are rooted in predictive analytics
34:53
techniques for that we can look at food
34:55
water financial storage
34:57
development and trade between various
34:59
countries and
35:00
try to increase the yield of dry land
35:02
crops using the
35:03
local sources but also regional
35:05
solutions across
35:07
i'll stop there thank you i'd like to
35:10
move on to our final speaker um abdi
35:14
tamurthy
35:14

he is the founder and ceo of consor
35:17
water technologies which
35:18
uses satellites and ai to measure soil
35:21
moisture
35:22
nutrient levels and other actionable
35:24
information about farmland and soils
35:26
to help farmers grow more with less
35:28
without using any hardware or soil
35:30
sampling
35:31
thousands of farmers worldwide currently
35:32
use concert water to save on water and
35:34
nutrients and increase the fertility of
35:36
their farms
35:38
audit is a stanford knight hennessey
35:40
scholar and holds a master's degree from
35:41
stanford along with two bachelor's
35:43
degrees from caltech he has also been
35:46
named a top founder in ai by
35:48
techcrunch and without with that i'd
35:50
like to welcome our final speaker thank
35:52
you
35:52
thank you for the kind introduction um
35:55
as just mentioned i am ultimately i'm
35:57
the founder and ceo
35:58

of constant water technologies uh where
36:01
we help farmers worldwide to grow more
36:03
with
36:03
less and i founded concert water
36:08
about four years ago and i kind of want
36:10
to narrate some of
36:12
our learnings from doing that and around
36:15
agricultural ai
36:16
where one of the key missions of
36:18
agricultural ai
36:20
at least in my opinion is to enable
36:23
farmers
36:24
to grow more with less and
36:27
while doing it in a sustainable manner
36:30
and
36:31
at scale so as you might be familiar
36:34
with ai
36:35
from other industries it's commonly
36:38
deployed
36:38
to enable scale to be unlocked
36:42
like for example when google or facebook
36:44
use ai
36:45
to target ads it enables them to scale
36:47
to billions of people
36:49

why can't that same thing be true in
36:51
agriculture as well can we design
36:52
solutions that
36:54
can scale dramatically to hundreds of
36:57
millions of farmers can we design those
36:59
kinds of solutions
37:00
it has been kind of the guiding
37:02
motivation here at least behind
37:04
how we have been approaching this area
37:07
and to give you a general idea of how
37:09
i like to think about ai at least in the
37:12
in its most
37:13
useful form in agriculture it's sort of
37:16
like this picture here
37:17
this picture might seem kind of a bit
37:19
abstract to you
37:21
if you take a second you'll notice that
37:24
there's these
37:25
purple stripes that are going
37:27
horizontally across the stream
37:28
at the screen but if you look a bit
37:31
deeper
37:32
if you look behind the stripes you start
37:33
to see something is present
37:35

and if you were kind of aware of
37:38
this location where this picture was
37:39
taken you might actually recognize
37:41
that's actually the university of maine
37:43
campus
37:44
in the background so this is essentially
37:47
one of the key purposes
37:49
of ai uh at least what it can
37:52
one of the big potentials of ai in
37:54
agriculture is that it can
37:56
unlock these hidden patterns that
37:59
human beings are not necessarily able to
38:01
unlock on their own
38:03
and then once you've unlocked that
38:05
you're able to derive
38:06
all sorts of value ai is able to
38:08
identify these hidden patterns that are
38:10
very hard for humans to do
38:13
of course there's also ai that can just
38:15
essentially
38:16
replace human beings but that's not the
38:18
kind that is
38:19
most sustainable for humanity in the
38:21
long term the best kind of ai at least
38:24

in
38:24
my opinion is ai that can unlock these
38:27
insights that you never
38:28
knew about before and thus gives you
38:31
completely original insights that can
38:33
change your operation change what you do
38:36
in a dramatic way and
38:39
today when we think about ai we usually
38:42
think about it
38:43
in terms of machine learning or
38:45
sometimes deep learning which is a
38:47
subset of machine learning this
38:49
maya is a very very broad term there's
38:50
many many different
38:52
ai techniques there's expert systems
38:54
there's uh all sorts of
38:56
techniques that are developed in the
38:57
past then when people generally talk
39:00
about
39:00
ai today they're usually referring to
39:04
machine learning when people generally
39:06
talk about ai and you might be familiar
39:08
with
39:08
some of the common methodologies used in
39:11

machine learning
39:12
and i'm going to illustrate in a moment
39:14
here
39:15
how uh how a uh how
39:18
all of these can actually find a role in
39:21
agriculture
39:22
to do very unique tasks that enable us
39:24
to unlock
39:25
all sorts of value so but before i go
39:28
into that let me just start out with
39:30
just a brief overview of each of these
39:32
types that everyone is clear
39:34
on what they mean so uh so the most
39:37
common kind of machine learning that you
39:38
might
39:39
normally think of is actually supervised
39:41
learning
39:42
the bottom right here and supervised
39:44
learning is where you have
39:45
a set of inputs and a set of outputs and
39:48
then
39:48
you train an ai model or a machine
39:51
learning model rather to be specific
39:53
to build a function that goes from the
39:56

inputs to the outputs if you gave it the
39:58
inputs
39:58
it can predict the outputs the computer
40:01
learns that function
40:03
that relates the inputs to the outputs
40:05
that is supervised learning when there's
40:07
inputs and outputs and you're building a
40:08
mathematical function
40:10
between them on the slightly other end
40:13
of the spectrum
40:14
there's unsupervised learning where
40:16
instead of having
40:17
inputs and outputs you just have inputs
40:20
and then you're trying to figure out
40:22
some relationship between the inputs
40:24
data without actually knowing
40:26
any reasonable outputs it's used to find
40:28
relationships and
40:29
between the data within the data that is
40:32
not otherwise
40:32
visible and unsupervised learning
40:36
also has interesting roles to play in
40:38
agriculture
40:39
but commonly you often think mostly
40:41

about supervised learning and not as
40:42
much about unsupervised learning
40:44
but still it's useful to have all these
40:46
frameworks in your mind
40:47
and thirdly there's reinforcement
40:49
learning
40:50
this uh this is what you might think of
40:53
like uh
40:54
like uh google's
40:58
go program playing the game go it became
41:00
so good at go
41:01
by through reinforcement learning
41:04
uh where reinforcement learning is
41:08
a slightly different paradigm of machine
41:09
learning where you're trying to
41:10
understand
41:12
how to optimize a certain task how can i
41:15
optimize to for example win a game
41:18
for example and all of these kinds of
41:20
scenarios find
41:21
interesting uses in agriculture so
41:23
without further ado when you think about
41:25
unsupervised learning
41:27
this is actually a a set of fields from
41:30

one of our clients actually at concert
41:32
water technologies here you can see that
41:34
this client has
41:36
several forms like dozens of individual
41:38
fields
41:40
however the reality is that you don't
41:42
often when you're on the farm you don't
41:44
often have
41:45
unlimited resources to plow into these
41:48
unlimited fields
41:50
you only have a limited set of resources
41:52
how do you allocate those resources in a
41:55
good manner so that you optimize various
41:58
conditions on the farm
41:59
one way that you can find out actually
42:02
is
42:02
by doing unsupervised learning on these
42:06
fields themselves to find
42:07
patterns and groupings within these
42:09
fields uh
42:11
natural groupings which then to those
42:13
groupings you can
42:14
then decide to apply certain
42:16
interventions like for example this is
42:18

just a naive guess from a
42:20
human eye perspective ai might pick up
42:23
further things
42:24
uh if you feed it with large amounts of
42:26
satellite data for example here you see
42:28
that these
42:28
fields seem to be slightly greener these
42:30
fields seem to be
42:31
slightly redders these seats are
42:33
slightly yellower
42:34
those might be natural ways to break up
42:37
the these fields in order to manage them
42:39
in a smaller chunks but there's a
42:41
variety of things that can be done here
42:43
depending on what is the final objective
42:45
for the grower is it yield maximization
42:47
reduction of disease
42:48
whatever is the objective uh the
42:51
unsupervised learning can give get you
42:53
a first step at understanding what are
42:55
these various kinds of groupings
42:57
but other than that unsupervised
42:58
learning is probably still quite in its
43:01
infancy from its applications in
43:03

agriculture because
43:05
of uh we just need to find the right
43:07
problems to apply to
43:08
so without further ado we come to
43:10
supervised learning
43:12
is probably as i mentioned the most
43:14
common thing that most people think
43:15
about when it comes to machine learning
43:18
there's two flavors of supervised
43:19
learning there's classification problems
43:22
where you're simply deciding whether
43:25
whether it's a cat or a dog is what
43:29
google's video ai would do what we are
43:32
doing
43:33
here is deciding between various classes
43:35
in agriculture
43:36
about what whether uh whether something
43:40
falls into one bucket or another bucket
43:42
as i'll show you in a bit
43:43
and regression is when and regression
43:45
actually quite common in agriculture as
43:47
well
43:48
uh much more common i'd say than in the
43:50
general
43:51

uh general ai in general uh when
43:54
regression you're trying to predict a
43:57
quantitative variable
43:58
an actual number as opposed to a class
44:00
whether it's a or b
44:02
you're trying to predict is it zero
44:04
percent fifty percent or 100
44:05
of some property whatever property is so
44:08
in a
44:09
classification one of the very very very
44:11
common use cases
44:13
of ai in agriculture which has actually
44:15
gotten quite a reasonable level of
44:17
adoption actually currently
44:19
this is not something that we do at
44:20
concert water but we find it very
44:21
interesting
44:23
to see the levels of adoption that have
44:24
been reached is actually in
44:26
using your phones to take pictures of
44:29
diseased leaves or disease plants
44:32
and then an ai can simply classify and
44:34
say
44:35
what is the disease or with some level
44:38

of
44:39
accuracy it can say what is the disease
44:41
that's afflicting your plant
44:42
you don't need to be an expert in
44:44
agronomy and understand
44:45
all of the various diseases that afflict
44:47
your plant
44:48
and as long as the system is trained
44:52
this uh the apps that are out there are
44:54
trained for those particular conditions
44:55
they can identify directly you don't
44:57
need to call up your agronomist to get
44:58
this information
45:00
uh it can find this patterns in the leaf
45:02
directly just by taking
45:04
pictures and then once you have that
45:05
picture it can identify
45:07
uh it can identify with some accuracy
45:09
what are the conditions and then you can
45:11
take the appropriate interventions
45:13
to reduce that the risk that that
45:16
disease poses to
45:17
the farming operation so that's a very
45:19
very interesting application
45:21

and and there there have been data sets
45:23
of various pictures and also
45:26
disease classifications that have
45:27
already been collected by various
45:29
labs around the world agricultural labs
45:31
and using these
45:32
people have been able to build deep
45:34
learning models in this case
45:35
to directly identify what are the
45:37
diseases uh
45:38
one other kind of application that we
45:40
have found actually more directly at
45:42
constant water is
45:43
by using satellites along with ai we're
45:46
able to identify
45:48
basically classify on a pixel level
45:50
where there might be anomalies
45:52
and potential diseased areas uh so
45:55
and what we're able to do beyond that
45:56
which is very important in agriculture
45:58
is you don't just want to have this
46:00
analysis you want to be able to present
46:01
the analysis in a way
46:03
that's understandable easy to use fast
46:06

to use for the farmer
46:07
who might otherwise find it hard to use
46:10
your technology if you can't actually
46:12
present it in a useful
46:14
manner this is not just true in
46:15
agriculture it's probably true in every
46:16
field
46:17
here to present the results in a manner
46:18
that are understandable uh here what
46:20
we're able to do is we have to identify
46:22
on a pixel level
46:24
where there might be potential diseased
46:26
areas or uh
46:28
are unhealthy areas and then what the
46:30
next layer of processing on top of that
46:32
is you
46:32
go to google maps and you place a marker
46:35
on those areas
46:36
automatically with code so then the
46:38
farmer can then just
46:40
walk to these markers and see what's
46:41
going on at that particular area
46:43
so what's basically going on here is
46:46
we're able to use a variety of satellite
46:48

bands
46:49
to pinpoint anomalies by using
46:52
supervised learning with classification
46:54
to classify pixels and decide whether
46:56
is this this pixel potentially the
46:58
location of an anomaly
47:00
and then direct farmers to those
47:02
anomalies
47:03
so that they can manage things more
47:05
effectively
47:06
and then moving on to into a regression
47:08
i think this is already mentioned
47:10
uh by uh by dr dave nani just before me
47:14
is one of the common things about
47:16
regression at least today common use
47:17
cases is actually in
47:19
crop yield prediction on a usually on a
47:22
county level or it could be sometimes
47:24
more granular than that
47:25
you can do crop yield predictions just
47:27
based on very basic
47:29
levels of satellite data you can get a
47:31
very good prediction of crop yields
47:33
which can then inform not only farmers
47:35

in that area but also investors in
47:36
general
47:37
when they try to decide whether
47:40
purchasing
47:41
corn contracts for this particular year
47:43
is a good investment decision
47:44
or not so all those kinds of efficiency
47:47
are being unlocked
47:48
by using satellites and ai kinds of
47:50
efficiency that were not present before
47:52
in the system
47:53
we're now coming more to uh where at
47:56
concert water we significantly use
47:58
supervised learning is in this uh
48:01
by using over 100 satellites throughout
48:04
the entire electromagnetic spectrum
48:06
from uv to radio waves which is the
48:09
input data and the supervised learning
48:11
if you make
48:12
we're able to combine that with the ai
48:14
models that we train using
48:17
large amounts of ground truth data in
48:19
the form of soil tests for example
48:21
actual lab soil tests
48:23

or sensor arrays around the world soil
48:25
moisture sensor rays
48:26
and convert that basic convert what the
48:29
satellite sees into actionable numbers
48:31
about
48:33
plants and soil information such as the
48:35
soil moisture levels
48:37
soil nutrient levels soil carbon levels
48:40
a variety of different things can be
48:42
understood by using
48:43
a large amount of satellite data coupled
48:46
with a large amount of ground truth data
48:48
upon which ai models are trained and
48:51
thus we are able to convert what the
48:53
satellite sees into these actionable
48:54
numbers
48:55
and why that's important is that
48:58
satellites actually take a huge huge
49:01
huge amount of data
49:02
like terabytes of data every single day
49:05
uh several terabytes of data
49:07
and overall like over the course of
49:08
several years we have many many
49:10
petabytes
49:11

of data huge amount of data human mind
49:14
cannot really comprehend that level of
49:16
data
49:17
and especially the trends shown in the
49:19
satellite data it's very very hard to
49:21
comprehend
49:22
very easily because what the satellite
49:24
sees is simply
49:26
raw numbers it's like your camera on
49:28
your phone
49:29
it just sees the counts of photons that
49:31
come off of the earth and everything
49:32
else is a derived product on top of that
49:34
just the count of photons what we are
49:36
able to do with ai is basically
49:38
convert those raw numbers into
49:41
actionable numbers
49:43
which the computer system the ai the
49:45
machine learning model
49:46
trains but trains to understand by
49:49
looking at the satellite data so very
49:51
classic
49:52
supervised learning going from inputs to
49:54
certain outputs they are
49:56

very relevant for farmers to manage
49:58
their operations
49:59
more efficiently and the best part is
50:02
that
50:02
it's not it's actually not like having a
50:04
soil sensor or a lab test because we're
50:06
able to do
50:07
uh we are able to actually use satellite
50:09
data to get things at an even granular
50:12
resolution you could even get like 10
50:14
meter less than 10 meter even three
50:16
meter
50:17
and uh in uh in a comma in a customer
50:20
units three meters would be 10 feet
50:22
so even at 10 feet resolution you can
50:25
get this information
50:26
uh using satellites coupled with ai you
50:30
can get information at that level of
50:31
resolution
50:32
so all sorts of new things are unlocked
50:34
a new possibilities
50:36
ai is unlocking all sorts of new
50:38
possibilities as opposed to
50:40
replacing existing possibilities and
50:42

just before we conclude here a quick
50:43
note about reinforcement learning
50:46
i personally feel uh reinforcement
50:48
learning is one of the
50:49
most important up and coming ways do you
50:52
place ai here
50:53
in agriculture because it's very
50:54
important from the adoption standpoint
50:57
which uh
50:58
uh which was mentioned the very first
51:00
talk in our sequence here
51:02
uh so uh one of the most basic kinds of
51:04
uh
51:05
process optimization leveraging
51:06
reinforcement learning has already found
51:08
adoption
51:09
is actually in indoor forms because all
51:12
of the variables are completely
51:13
controlled
51:14
in indoor forms and hence it's a it's a
51:16
slightly easier problem than outdoor
51:18
forms
51:18
when all the variables are controlled
51:20
but when you actually go to outdoor
51:22

farms there are very very interesting
51:23
applications
51:24
like for example in this case we are
51:26
showing i guess some of
51:28
our or some of our partners at constant
51:30
water for example tow gill
51:31
uh irrigation controller units these
51:34
controller units sit on the farm
51:36
and what they're able to do is they're
51:38
able to
51:39
use our apis on the cloud console waters
51:42
apis
51:43
to implement ai on the farm and
51:45
essentially automate the farm
51:46
but that's not the interesting part
51:48
where reinforcement learning comes in
51:50
the way the place where reinforcement
51:51
learning comes in is once you have a
51:53
unit like this
51:54
we are able to use reinforcement
51:56
learning
51:57
to optimize an objective such as uh
52:00
such as maximizing your yield that might
52:03
be the most important
52:04

thing for the farmer maximize your yield
52:06
or it could be sometimes
52:07
reduced water use uh you want to
52:09
minimize the water use there's various
52:11
objectives depending on the farmer
52:12
that's interesting for optimization a
52:15
reinforcement learning scenario
52:16
but once you have this kind of setup you
52:18
can then start to think about
52:20
reinforcement learning
52:21
in just optimizing the daily decisions
52:24
uh
52:24
water applied nutrient applied using
52:27
satellites in ai
52:29
and crucially on the behavior change
52:30
perspective which behavior change is a
52:32
very very hard thing to achieve in
52:34
in agriculture what reinforcement
52:36
learning can do for you is it can adapt
52:38
to the
52:39
to the farmers existing practices it can
52:42
essentially learn
52:43
how the farmer manages their farm on a
52:45
daily basis based on all of these inputs
52:48

and then help the farmer to slowly ease
52:51
them
52:52
into the efficient scenario provided by
52:56
the supervised learning models like for
52:58
example i'll give you a real example
52:59
here
53:00
we had some farmers who are using uh 1
53:03
000
53:04
or yeah so we 10 000 cubic feet of water
53:08
per hectare
53:09
per year uh is what they were commonly
53:12
using
53:13
and then we had them what our models
53:15
were initially suggesting to them is you
53:16
don't need ten thousand you only need
53:18
six thousand
53:19
uh when you do all these calculations
53:21
but then there's
53:22
often going there's often some push back
53:24
uh because you're going suddenly a forty
53:26
percent decrease i'm so worried that
53:28
that's something that's going to happen
53:29
to my crops
53:30
the solution to that is actually to go
53:32

from 10 000
53:33
to 1900 9800
53:38
9700 slowly ramp it down and slowly ramp
53:41
it down
53:41
as per the farmer's existing practices
53:44
that he slowly eases
53:45
into an optimal scenario uh where
53:49
you eventually reach six thousand you
53:50
don't drop to six thousand overnight
53:52
this is a gradual behavior change and
53:54
this is probably the most effective way
53:55
to achieve behavior change in
53:57
agriculture at least that's what we
53:58
suspect today
53:59
uh by enabling that gradual behavior
54:01
change which can also be unlocked by
54:03
this
54:03
these kinds of ais you're able to ease
54:06
them ease the farmers into new
54:07
technologies without it being an
54:09
aggressive
54:10
uh change that they're hesitant to adopt
54:14
so before i conclude here i just want to
54:15
leave you with one last parting thought
54:17

is all this is only possible if you have
54:20
some kind of training data
54:21
on which you can build machine learning
54:23
models so where does this data come from
54:26
uh there's a thought that i want to
54:28
leave you with uh here
54:30
because it's the most important part as
54:31
part as with any ai you need data to
54:33
make things happen
54:35
there's many creative data sets out
54:37
there though there's many
54:38
hacky data sets if you made like you can
54:40
put together a data set from multiple
54:41
different sources you have a very
54:42
interesting data set
54:43
that can then unlock new value but where
54:46
does data come from that's a crucial
54:47
question
54:49
and thank you for having me here today
54:50
and happy to take any questions if
54:52
there's any time remaining
54:53
here thank you audit and thank you to
54:57
um nourish and stephen as well i think
55:00
we're getting short on time
55:02

um so i just wanted to thank each of our
55:05
speakers
55:07
for their excellent overview i think we
55:09
covered quite a bit of ground
55:10
between the three of you i guess um one
55:13
question i might have is
55:14
as climate change worsens would you
55:16
anticipate that things become
55:18
more unpredictable and if so what is the
55:22
is there time to respond in something
55:24
like a agricultural time scale
55:27
to correct issues if you will and to
55:29
actually
55:30
will those predictions become less
55:32
accurate as the climate worsens
55:34
i guess i could take a quick stab with
55:36
it i guess is uh
55:38
yeah so so the models will get outdated
55:41
over time
55:42
so that that is where you have to
55:43
retrain the models uh
55:45
uh so uh there's many strategies for
55:48
that you could
55:49
completely retrain the models entirely
55:52

all the time like every few years
55:53
or it could be a kind of like uh online
55:56
machine learning as they like to call it
55:58
kind of method if you if you set up the
55:59
models that way to begin with
56:01
is uh from using further inputs from the
56:03
ground it could automatically be getting
56:05
better
56:06
uh with time so that's crucial though
56:08
the models have to
56:09
keep getting updated you can't even
56:11
today like uh
56:13
i wouldn't say it's reasonable to use
56:14
models developed in the 1980s
56:16
for doing work today already so
56:19
things change does happen but sort of
56:22
the good thing is that
56:23
climate change is slightly longer time
56:25
scale event it's not something that
56:26
happens like overnight
56:28
so the model that we developed today can
56:31
probably be used definitely for this
56:32
season
56:33
for the next season maybe even or even
56:35

for the next season after that
56:36
then of course there's probably already
56:38
better data sources out there so you're
56:40
anyway going to retrain the model but
56:41
it's very crucial to
56:43
a retrain every several years you can't
56:45
use the same thing for
56:47
100 years very much i wish we had more
56:50
time
56:51
the talks were very interesting and the
56:54
luckily
56:55
a video recording of this will be
56:57
available on the umaine ai webinar
56:59
website
57:00
and with that i'd like to speak all and
57:02
thank again all of the speakers and also
57:04
to the attendees for joining us
57:06
and as a reminder the next ai webinar in
57:09
our series aim healthcare
57:10
is scheduled for thursday may 6 from 12
57:14
to 1 pm eastern time
57:16
and with that thank you all for your
57:17
attendance and i hope everyone has a
57:18
good day

The University of Maine in Orono is the flagship campus of the University of Maine System, where efforts toward racial equity are ongoing, as is the commitment to facing a complicated and not always just institutional history. The University recognizes that it is located on Marsh Island in the homeland of the Penobscot nation, where issues of water and its territorial rights, and encroachment upon sacred sites, are ongoing. Penobscot homeland is connected to the other Wabanaki Tribal Nations — the Passamaquoddy, Maliseet, and Micmac — through kinship, alliances, and diplomacy. The university also recognizes that the Penobscot Nation and the other Wabanaki Tribal Nations are distinct, sovereign, legal and political entities with their own powers of self-governance and self-determination.