REMOTE SENSING, AI AND INNOVATIVE PREDICTION METHODS FOR ADAPTING CITIES TO THE IMPACTS OF THE CLIMATE CHANGE
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ABSTRACT:

Urban areas are not only one of the biggest contributors to climate change, but also they are one of the most vulnerable areas with high populations who would together experience the negative impacts. In this paper, I address some of the opportunities brought by satellite remote sensing imaging and artificial intelligence (AI) in order to measure climate adaptation of cities automatically. I propose an AI-based framework which might be useful for extracting indicators from remote sensing images and might help with predictive estimation of future states of these climate adaptation related indicators. When such models become more robust and used in real-life applications, they might help decision makers and early responders to choose the best actions to sustain the wellbeing of society, natural resources and biodiversity. I underline that this is an open field and an ongoing research for many scientists, therefore I offer an in depth discussion on the challenges and limitations of AI-based methods and the predictive estimation models in general.

1. INTRODUCTION

Climate change is becoming a bigger treat for the wellbeing of all living beings on the planet day by day. High ecological stress and the heat islands created by urban areas create a huge impact not only in the urban areas themselves but also in the surrounding rural areas because of the heat island impact. While being one of the biggest contributors to climate change, cities are also one of the most vulnerable areas to the negative impacts. The United Nations predicts that before 2050, 74% of the European population and 68% of the world population will be living in cities (United Nations, 2018). Regarding these figures, if the climate change triggers of the urban areas are not well-identified and changed, a large number of the world population, and the biodiversity within and at the surrounding of the urban areas will be in existential stress.

For identification of the climate impacts of the urban areas, many IT -infrastructured (also called ‘smart’) cities, have been putting efforts and resources to collect a good amount of data which might be helpful to identify the climate stress factors. Thus in many smart cities, citizens, government institutions, industry and scientists share data for the benefit of all (this relation is presented with the ‘Quintuple Helix model’ (Carayannis et al., 2012)). Obviously, this leads to a great amount of data collection and the need for machine learning (ML) or artificial intelligence (AI) models which can use the data for extracting climate and land-use related indicators, which could also be used for creating predictive models. We also need to acknowledge that not all cities are able to collect such big data from distributed sensors and from the data sharing parties mentioned. Therefore, when it is possible, extracting indicators from satellite images would help to achieve predictive models which could be used at any city globally.

If climate change and human activity related indicators are extracted from remote sensing images, with power of AI methods, there would be possibilities for;

- creating rapid maps of land use and environmental resources in large scales
- making predictions about future states of extracted indicators
- simulating “what happens if” scenarios for disaster prevention
- identifying abnormal situations (outlier identification)
- explaining the impact of the indicators with eXplainable AI (XAI) methods
- identifying the relation between human activity, climate change and biodiversity related changes

The list above could be extended further, however for now I will be limiting my discussion with these possible applications. Considering that, when such AI models are developed, they must immediately be used in real-life applications because of the climate emergency, in this article I would like to discuss also the following practical topics;

- Data collection
- Feature extraction
- Model selection
- Generalization
- Reproducibility
- Maintainability

Furthermore, I approach from a sustainable smart city development perspective, keeping the sustainable development goals (SDGs) and ethical & responsible use of AI as the ultimate judgement criteria for each of my suggestions. Because of their high scalability, low-cost and reliable data collection properties, I focus on possibilities of using satellite images as data source. In the rest of the paper, I focus on answering the following research questions.
1. How remote sensing images and AI can help to extract land use and environment related indicators to monitor climate adaptation of cities?
2. How fine scale innovative climate modeling and prediction models could be achievable?
3. What are the limitations of remote sensing images and AI models for good climate adaptation monitoring and for making good predictions?

I assume that the reader acknowledges that the current climate change that we are in (anthropogenic climate change) is mainly caused by humans (i.e. daily consumption and commuting choices, industrial activities). Therefore, one of my main ambitions with this paper is to suggest observation systems which can highlight the relation between the human land use and the environmental changes. In this way, I hope that the upcoming climate change related crisis could be understood and the negative impacts could be decreased by changing activities which contribute to this environmental stress. Nevertheless, expectations from AI models about solving climate related problems should be realistic. In the discussion section, I discuss both powers and weaknesses of AI and further open topics which prevent proposing more robust AI models for the time being.

2. BACKGROUND

2.1 Climate models, remote sensing and the impact of the AI models

As the Intergovernmental Panel on Climate Change (IPCC) has been warning in its reports, climate change is likely to bring devastating consequences to the health of humans and animals, to social living and to environmental resources (Field et al., 2014). The accelerated speed of climate change could be slowed down with significant reduction of greenhouse gas emissions and the heat island impacts created by the urban areas (O’Neill et al., 2018). Levels of carbon dioxide in the atmosphere stayed in a narrow range over the last million years. In the last hundred years, they have risen from 280 ppm to 400 ppm. These changes in CO2 concentrations closely match with the human-made developments within the urban areas (Berkeley, 2014).

In his study, Satterthwaite said “Do not blame cities” (Satterthwaite, 2008) for being the biggest stressors of the climate change because oil refineries, deforestation activities, animal agriculture, heavily chemical and fossil fuel using agriculture, commercial transportation etc. are happening outside of cities. However, the fact that we shouldn’t ignore is that those activities are happening for bringing food, fossil fuel and other needs of the highly industrialized and dense populations within the cities. What I mean is that, even though such big climate stressor activities are happening outside of the cities, they are still happening because of the lifestyle and demand within the cities. Therefore, I still find it valuable to focus on cities in climate related studies.

Observation of the climate change stressors of the urban areas requires observation of the conditions of these areas in multiple aspects. Soil/water surface temperatures, atmospheric events, vegetation/ice cover are just a few of them. Many climate models can predict future states of the climate for a region using these parameters (Randall et al., 2007). Two major models are frequently used in this field; Earth System Models (ESMs) and Global Climate Models (GCMs) (McSweeney and Hausfather, 2018). ESMs include all the features of GCMs and also simulate the carbon cycle and other chemical and biological cycles that are important for determining the future concentrations of greenhouse gases in the atmosphere. ESM looks at the environmental indicators in large grids and it is able to make predictions for large regions in an acceptable performance. However, when it comes to make prediction for a finer scale (like looking at a city-size area), the predictions become less accurate. This is the reason why we frequently see news articles telling that ice sheet of a certain area is melting faster than what scientists have expected (World Economic Forum, 2020). In their climate model assessment report, Bader et al. (Bader et al., 2008) discussed this issue. They mentioned that the global models (or large grid models) do not provide very accurate results when they are used at a smaller region. If the models are going to be used in a city-size focus region, the model parameters need to be adapted regarding the human-made developments and activities in that area. They add that, even then these fine-tuned models will work for the focus regions only for a short time frame, because they will be missing the relation to the global changes. In my understanding, Arctic ice melt and Amazon rain forest damages would eventually make an impact in a far away region. However, the fine-tuned local models would miss this crucial connection to the global events. Last but not least, Bader et al. have addressed the extremely high time consumption and costs of fine-tuning climate models for every small area globally.

To make models more successful for local applications, Asch et al. (Asch et al., 2016) suggested that the most suitable way to make predictions would be simulating many different scenarios about the indicators of a specific region. Kitchin et al. (Kitchin and Sichler, 2021) addressed various different type of data that should be collected in smart cities for better understanding of the causes and effects between the activities of large populations and the environment. They also discussed challenges of collecting such specific data variety within urban areas. Many climate scientist agree that representative urban region indicators for tracking human-made developments and environmental changes should be added into climate models. These models could also be helpful for understanding whether a city is developing within environmental limits or not. For this purpose, Caird et al. (Caird and Hallett, 2019) suggested that ISO smart city indicators (ISO 37122:2019 Sustainable cities and communities, Indicators for smart cities) which could be useful to identify what measurements should be collected as a big data in order to track sustainable development of cities.

Earlier in the literature, researchers focused on collecting IoT data from cities in order to create big data to measure the sustainable development (Giang et al., 2016) (Su et al., 2011). Usage of remote sensing data for sustainable smart city development measurement has been considered by some scientists as well. Bonafoni et al. (Bonafoni et al., 2017) showed that it is possible to measure surface heat stress of cities using satellite sensors in order to model and track the changes of the urban heat island effect. Milojevic-Dupont and Creutzig (Milojevic-Dupont and Creutzig, 2021) have suggested that remote sensing images could be used for measuring air quality, biomass, carbon, soil/water surface temperatures, built up area growth and water quality/levels. It is still not clearly identified how to validate and generalize these methods and what universal measures to use in order to define “climate adaptation” and “sustainability” of the smart cities.

Guemes et al. (Guemes et al., 2021) have shown that fine detail
climate models can be modeled with AI models when coarse measurements are collected. This study increases trust in future possibilities of fine detail climate modeling using remote sensing images and AI models.

In this paper, I propose methods to extract urban development and environmental indicators from remote sensing images which might be useful for observing climate adaptation of cities. Besides, I suggest an AI framework which might be helpful for creating fine detail climate models for smaller interest regions and to predict their future climate status. I discuss that satellite images not only provide large scale (planet wide) observation possibilities but also they offer the most sustainable observation solution without need of in-situ sensor and embedded system installation.

2.2 Smart city indicators

European Environment Agency (EEA) has published indicators which could be used for observing the sustainability status of the smart cities (European Environment Agency, 2019). As in the example given in the Figure 1, EEA has suggested that correlation between the ecological footprint and human development indices (HDI) could be used for measuring the sustainability levels and climate adaptation of cities. Detailed mathematical process for calculation of these ecological footprint and HDI indices has been introduced in the EEA technical note document in detail (EEA Technical Notes, 2018).

In this figure, 'Ecological Footprint' is the metric that shows how much nature we have and how much nature we use. Ecological footprint calculation with IoT data is explained within the documentation in detail (Network, n.d.). The horizontal axis, ‘Human Development Index (HDI)’ is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and having a decent standard of living. The HDI is the geometric mean of normalized indices for each of these three dimensions (EEA Technical Notes, 2018). When these two indicators (one about the human development activities and one about the natural wellness), a plot like the one in Fig. 1 can help to track the climate adaptation of a city assuming that climate adaptation requires a good balance between these two indicators (the green area in the figure). Besides, these indicators could contribute to developing fine tuned climate models which could be used in prediction of future climate status of the city.

Unfortunately, EEA indicators cannot be used in an automated framework for the time being, because of the complexity of the parameters which are used to calculate the ‘Ecological Footprint’ and ‘HDI’ indicators. Obviously, a parameter like human health or human long life cannot be extracted from satellite images. It could be possible to automate a model with the model development process if these parameters are offered with an API from each city which is not realistic for our times (as different cities have different budgets to construct such a database and API).

For observing such ecological and human development indicators, the International Organization for Standardization (ISO) proposed a set of indicators which could be standard for each city (ISO37122, 2019). However, the ISO indicators also rely on availability of a database provided by the city.

In order to discuss automation possibilities of the ecological and human development observation process, being inspired by the EEA and ISO indicators, in Table 1, I have listed the city indicators which could directly or indirectly be observed by satellite images. When it is possible to measure indicators directly as it was described within the documentation, the indicator is labelled as ‘direct’. When it is not possible to measure the indicator directly as it is described, however when it is possible to extract highly correlated measurements, the indicator is labelled as ‘indirect’. For instance, if the city keeps the number of people who have completed a high education and provides this number with an API, that could be a ‘direct’ IoT measurement. As another example, the economy of a city cannot be directly known from a satellite image, however it could be still possible to have an idea by looking at the building and road construction. This kind of urban development could give some indicators about the economical status of the area. In other words, 'Direct' refers to the methods which directly look at the indicator value, 'Indirect' refers to the methods which look at other properties within data in order to estimate the indicator value. Assuming that all the indicators could be provided as ‘Direct’ measurements via a city database if there was such smart city infrastructure available, remote sensing data enables less measurements and more indirect indicators than IoT measurements. However, remote sensing data would have advantages over IoT data such as having less privacy concerns, providing large area observations and providing opportunity to repeat the measurements consistently as the satellite observations are done automatically. Satellite image based observation also provides advantage for the less developed cities because of not demanding any sensor installation and back-end development for creating a database and API.

3. METHODS

In order to answer the research questions, I propose designing the following three modules:

1. Extracting land use and ecological indicators from satellite images
2. Climate adaptation observation
3. Training predictive models
4. Proposing a finer scale climate model

I imagine the relation between these modules as in Fig. 2. Next, I discuss development of each module.

3.1 Extracting land use and ecological indicators from satellite images

For building a successful model, I believe it is important to follow the ecological footprint index and HDI formulas suggested by EEA. In Table 1, I have discussed availability of the indicators which serve as the parameters of these formulas when the satellite images are used as a resource. Even though it looks promising to see that satellite images could provide either direct or indirect measurements for most of these parameters, it still needs much wider research to understand how to calibrate and normalize the satellite image processing based indicators before providing their values to these formulas. For now, I need to leave this study to the next step of my future work and I need to choose simpler formulas to replace the ecological footprint index and HDI.

For the sake of designing the first practical model, I chose a simple indicator which might roughly represent HDI. This was
Figure 1. Correlation between Ecological Footprint and Human Development Index (HDI). HDI values above 0.8 are defined as "Living well". Ecological footprint values below 1.7 are defined as "Living within environmental limits". The value of 1.7 refers to the average biocapacity per person globally in 2014. (Image adapted from: European Environment Agency https://www.eea.europa.eu/data-and-maps/figures/correlation-between-ecological-footprint-and).

Figure 2. Modules proposed in this study towards answering the research questions.

For observing how much the city is aligned with the climate goals, it would be a good idea to use a plot like in Fig. 1. For our simplified-index-based setup, the vertical axis should be represented with the inverse of the urban green index (since in the original plot, it represents the footprint, not the greenness) and the horizontal axis should be represented with the land development index. The biggest challenge would be to calibrate and normalize these two indices. To this end, I would suggest picking two cities from the latest SDG ranking report (United Nations, 2021). One of these two cities should appear in the lowest ranking and another should appear in the highest. In this way, when the urban green index and the land development indices are calculated by using satellite images of these two extreme (good and bad example) cities, their index values can be

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3.2 Climate adaptation observation

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used for normalizing other cities’ index values between $[0, 1]$. While plotting, to the vertical axis, urban green index should be subtracted from 1 to represent the footprint instead of the greenness. Finally, the green region of the Fig. [1] will appear in our simplified climate adaptation plot to show whether the city is in the green area (living well and living within the environmental limits) or not. It would be another future research step to find good threshold values to represent the boundaries of this green area in the satellite based measurement plot. For now, the threshold values could be assumed as the 20% of each axis, similar to the EEA index based plot. Since after the normalization process, the vertical and the horizontal axis values will be between $[0, 1]$, the horizontal axis threshold value would be 0.8 and the vertical axis threshold value would be 0.2. Nevertheless, these satellite based observations must be repeated on many cities, in order to determine whether these threshold values are still representing the climate adaptation area or not.

### 3.3 Training predictive models

In ‘forecasting’ applications AI uses a time series of historical data to learn parameters of a good fitting model which represents the trend of this data in time. After the model is trained (parameters are learned) the same model is used to find the data points in any future time. Thus, when the urban green index and the land development index that we have used in the climate adaptation observation module are collected for a time period (for instance every month for a city), it would be possible to use ML or AI models to create a prediction model to estimate future values of the urban green index and the land development.

Before choosing the right prediction model, it would be a good idea to visualize some of the existing training data to see how the trends look like. If the trends in general look like they could be represented with a polynomial function, it would be so much easier to develop a regression model with ML algorithms. This process would also require less training examples. On the other hand, if the trends of different cities do not look like showing a similar increase or decrease and if they look too complex to be presented by a polynomial function, it would be a better idea to use an AI method for predictive modeling. For such a case, training a Long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) would help achieving more robust results. LSTMs are successful in remembering what changes happen after significant events in the past and they are less likely to be affected by the noise in the data which might be because of a short term and insignificant event.

### 3.4 Building finer scale climate models

“All models are wrong, but some are useful. - George Box”

In the background section, I have discussed the strengths and weaknesses of the existing climate models which have been used for decades. To summarize:

- The existing climate models make reliable predictions (Carbon Brief, 2021).
- The existing climate models lack great amount of detail, having a having a coarse spatial resolution with a grid-cell size on the order of $2.5^\circ \times 2.5^\circ$ (approximately $275 \times 275$ km$^2$), which is far too coarse for identifying impact of the human activities, land use and the biodiversity threats. (Flint and Flint, 2012).

- AI-based methods might help to develop finer scale models.

Cheng et al. (Cheng et al., 2016) proposed a new AI model called ‘wide and deep learning’ which significantly improved recommender systems. They have provided a TensorFlow API to speed up research in this field (TensorFlow, 2021) which allowed more researchers to test the successful practice of combining features of a deep neural network and the raw input together. The reason is that some input information might need to be processed in the deep neural network to find the most meaningful information within and some input information might be significantly important as they are. In our case of fine scale climate modeling, I believe it is also beneficial to consider such a model as illustrated in Fig. [3]. As a future work, I believe that not only the urban green index and the land development index which we used for the simplified modeling, but all the indicators that we have proposed in Table [1] should be used as the local indicators (deep model input) and the existing climate model parameters should be used as the global indicators (wide model input). As an example, such a model could be trained for predicting the local temperatures or biodiversity variety. It could also be a part of the future work to investigate the importance of both local and global indicators using eXplainable AI (XAI) techniques.

### 4. DISCUSSION

In the following subsections, I discuss research questions in light of the methods proposed in this study.

#### 4.1 How remote sensing images and AI can help to extract land use and environment related indicators to monitor climate adaptation of cities?

Remote sensing images can help by monitoring the climate adaptation of the smart cities. AI allows predicting further states of the environmental and land development indicators of the cities. Besides, innovative AI models (like the use case of the wide and deep learning method) can help with achieving finer scale climate models to observe cities’ climate indicators more efficiently.

When the modules in Fig. [2] are developed, the outcomes of the modules can help with the SDG’s which are listed in Table [1]. Fig. [3] shows the sustainable development goals which can be supported with satellite images and AI methods together. The radar chart in the figure illustrates how much help can be provided to each SDG. Herein, if the indicator extraction method is indicated as 'Indirect' in Table [1] the contribution to the SDG is represented as 50%, otherwise the contribution is represented as 100%.

#### 4.2 How fine scale innovative climate modeling and prediction models could be achievable?

As one of the potential solutions to achieve finer scale climate models, herein I proposed an AI method known as wide and deep learning. However the performance of such models should be further investigated in future studies.
4.3 What are the limitations of remote sensing images and AI models for good climate adaptation monitoring and for making good predictions?

Limitations of the remote sensing and AI based solutions for the climate adaptation and prediction topics suffer from two main issues. One is the practical difficulties of building a fully automated framework with AI and the second is the unknowns about climate change and climate modeling science.

Table 2 summarizes the discussion on the challenges and limitations of the proposed methods, besides suggesting some potential solutions to investigate the topics further.

4.3.1 Further open topics

We have talked about the challenges and limitations of designing an automated climate observation framework based on remote sensing and AI methods. We could call these challenges and limitations as the ‘known knowns’. Finally, I would like to remind that in the field of climate science there are also ‘known unknowns’ (I will mention the known unknowns that I am aware of), and there are many other ‘unknown unknowns’ waiting to be identified by researchers.

Domino effect and self-reinforcing feedback loops

One of the ‘known unknown’ is the domino effect of the threshold events. Steffen et al. (Steffen et al., 2018) discussed that there are several temperature thresholds which will trigger climate events which start triggering other climate events on another side of the earth. This is explained as the domino effect in their study. To the best of my knowledge, such self-reinforcing climate triggers are not considered in any climate model. Thus, any predictive model that we have designed so far, will be incapable of predicting the conditions after these events are triggered.

Reliability of the satellite based observations

In their recent study, Jia et al. showed that satellites have been underestimating the cooling needs of our planet (Hailing et al., 2021). The reason is that satellite image based cloud cover calculations are mostly considering the lower clouds since they generally work relying on ‘cloud shadow detection’ algorithms. Higher clouds and aerosol masking effects are not considered in the current earth radiation needs in order to keep the global average temperatures below 2C degrees (Andreae et al., 2005). In short, the earth would need more cooling than the satellite image based calculations if the higher clouds and the aerosol masking were not there. Considering all climate adaptation indicators are extracted from satellite images, we should consider high uncertainties in any AI model which is used for finding trends.

Changing behaviour of the same environmental components

Another uncertainty comes from unknown behaviour of the changing environmental components when the temperatures change. While making our projections for the future, we assume that there is no change about how much CO2 could be stored in oceans and in soil. However, researchers showed that even a 2C increase in soil temperature will make a significant reduction in the soil storage capacity of the soil. The same applies for the oceans’ CO2 storage capability. This means that even if we managed reducing our CO2 emission, there will still be increased amount of CO2 in the air (P et al., 2003).

Changing behaviour of humans and land use activities

With increasing heat, more residential, business and other buildings have started using multiple air conditions. Even in the countries where people have cycling habits, in times of heat waves cycling is seen unsafe because of the danger of a heatstroke. Therefore more people started commuting with air conditioned cars even for short distances. In addition to that, after such an unexpected pandemic, most of the vaccines required special refrigerators to keep them in good conditions. These behaviour changes (and many unexpected to come) might have high potential to impact climate change.
5. CONCLUSIONS

In this article, I have discussed automation possibilities of climate adaptation observation of cities using remote sensing data. I have proposed methods where AI can help for making predictions and also for building finer scale climate models. I have discussed challenges and limitations of building the proposed models. My next steps will be focusing on creating demonstrations in some test cities within the Netherlands.

“If I had more time, I would have written a shorter letter. - Blaise Pascal”

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I have to declare that I do not have my educational background in the field of climate science or ecology. My expertise lies in applying computer vision and artificial intelligence techniques to remote sensing data for earth observation. Since my earth observation applications are frequently related with the climate related changes that the urban areas and the vegetation are going through, I have been doing a wide spectrum of literature search in the field of climate change. If I have made any claims which contradict the scientific findings of the climate and ecological experts, I will be pleased to know and make changes in my publication if it is necessary for the soundness of science.

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| No | Smart city indicator                                      | Remote sensing | Method                                                                 | Examples                                                                 | SDG |
|----|-----------------------------------------------------------|----------------|------------------------------------------------------------------------|--------------------------------------------------------------------------|-----|
| 1  | Economy                                                  | Indirect       | Residence building shape and size, their gardens (swimming pools, golf courts, etc.) or slum looking texture can give indication about the economic status of a region. | (Kutter et al., 2016)                                                    | 8   |
| 2  | Education                                                | Indirect       | Crowdedness, greenness and development of the city (well organized buildings and large roads) might indicate higher ratios of well educated community. | (Li and Weng, 2007)                                                     | 4   |
| 3  | Energy                                                   | Indirect       | Building sizes and their estimated human capacity can be used to predict the amount of energy consumption. | (Liu et al., 2021)                                                      | 7   |
| 4  | Environment and climate change                           | Direct         | Satellite images can show the deforestation, ice and vegetation cover changes. | (Dutrieux et al., 2012)                                                  | 15  |
| 5  | Health                                                   | Indirect       | Satellite images can help to predict availability of food resources and their variety. This might indicate the type of malnutrition and potential illnesses in the area. Besides, the air quality observation might give ideas about the respiratory diseases. | (Bondi et al., 2020), (Alvarez-Mendoza et al., 2019)                    | 3   |
| 6  | Recreation                                               | Indirect       | Convolutions neural networks (CNNs) can be trained to recognize parks and other recreational buildings/areas from satellite images. Nevertheless, many recreation activities are held indoors, therefore we labelled this indicator as an ‘Indirect’ one. | (Hu et al., 2016)                                                       | 3   |
| 7  | Safety                                                   | Indirect       | Incident locations can be labelled on a map and an ML algorithm can be trained to recognize potential incident locations by looking at road, building, green area indicating features. | (Najjar, 2017)                                                          | 16  |
| 8  | Telecommunication                                        | Direct         | Satellite images give possibility to identify towers which enable various communication channels. | (Nico et al., 2020)                                                     | 9   |
| 9  | Transportation                                           | Direct         | Computer vision, ML and AI methods can be used to extract road network, seaports and airports from satellite images. Besides, when Synthetic-aperture radar (SAR) images are available, they can indicate the motion direction and speed of the transport vehicles. | (Unsalan and Sirmacek, 2012), (Chen et al., 2018), (Hoppe et al., 2016) | 9   |
| 10 | Agriculture and food security                            | Direct         | Type of yield and their growth status can be recognized by satellite image processing and machine learning models can help to estimate how much yield will be available on which date. | (Sayago and Bocco, 2018)                                               | 2   |
| 11 | Waste                                                   | Direct         | Satellite images can provide visual information to detect amount of the waste in open waste collection areas. However, the collections in the close areas and the separability of the waste cannot be known. Nevertheless, the open area waste could provide some indication about the amount of the waste generated. | (Vambol et al., 2019)                                                   | 12  |
| 12 | Water                                                    | Direct         | Water quality parameters (i.e., suspended sediments (turbidity), chlorophyll, and temperature) can be identified by satellite images. | (Ross et al., 2019), (Ritchie et al., 2003)                             | 6, 14 |

Table 1. Smart city indicators to measure climate adaptation and some potential satellite image processing based methods to extract those indicators automatically.
Figure 4. The radar graph shows how remote sensing and AI based methods can contribute to each SDG. ‘Indirect’ impact is shown with 50% and ‘Direct’ impact is shown with 100% value on the graph. (The SDG poster is adapted from: United Nations Sustainable Development Goals official website: https://sdgs.un.org/goals)
| Earth data | Challenges | Solutions |
|------------|------------|-----------|
| Training data | The measurements which happened earlier cannot be reproduced | If it is possible to save measurements, it would be possible to repeat the experiments when new models are developed. However, tracking the time variance of all indicators around the world, would generate a very big data set which would cause other practical problems about storing data. |
| Test/Evaluation data | The satellite sensors are improved every few years. They provide higher quality and higher resolution images. However, changing sensors would create a challenge for the models which were trained with lower resolution and lower quality data in the past. | Models possibly need to be re-trained to prevent deterioration. |
| Model selection | Unfortunately, there is no formula which tells what AI/ML model to choose for each module. | The most common approach is to determine a few number of models which are assumed to be useful. This step, of course, depends on the intuition and experience of the developer. Afterwards, those candidate models could be compared in terms of their performance on training/testing data sets, their bias/variance and the number of the hyperparameters. When the response time is important, that could be taken into account as well. In environmental perspective, I believe that the developer must consider the trade of between the model performance and the hyperparameter numbers. |
| Generalization | One model might not be suitable to represent any city around the world. | It might be also possible to segment the cities depending on their geographic conditions and train a separate model for each segment. |
| Reproducibility | In practice an ML/AI framework should provide reproducible results. However, lack of reproducibility of the past test data might make this goal unachievable. | It would be possible to reproduce the results when the test data, model architecture and the model weights are stored properly. |
| Maintainability | Even though in many ML/AI problems, maintainability is one of the biggest challenges, for our application it might be less concerning, because of the high reliability of the satellite images which regularly make observations all around the world. The biggest maintainability might be the model deterioration. | Model deterioration might be overcome by re-training the models with new data in certain periods of time. |

Table 2. Practical challenges of implementing a remote sensing and AI based fully automated framework for observing cities.