Ethics for AIxEOxRS

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1. Introduction

The power of recent technical advancements in the fields of remote-sensing and earth-observation is not matched by ethical considerations of its use. Of course, ethical discussions in the field of geospatial data analysis are not new. As (Blakemore, 2004) points out, examples can be found as early as 1977. But back then, satellite imagery and geospatial software were only available to powerful companies and institutions of industrial states. That has changed. Besides increases in data volume, variety, availability, and quality, we can now get much more information out of the data, due to recent developments in Artificial Intelligence. Along with this power grows the potential for its use and misuse. This increase in ethical issues has not been matched by an increase in ethical considerations on part of the community.
Because of this, I believe, the topic of ethical use warrants further attention.
This present essay is my very personal attempt to reflect upon my work and collect my thoughts and findings on the ethical issues within the field I work in. Firstly, I will define and discuss the scope, aim and structure of the essay. I will then review, in succession, existing ethical codes in the field, some of my own study projects, and relevant literature. I will conclude with a summary of my personal learnings.

Scope

The scope of this essay is the Applied Ethics of the utilisation of Artificial Intelligence for Remote-sensing-based Earth Observation. From now on I will refer to the individual components as RS, EO, and AI, and to their intersection as AIxEOxRS. The two first terms **Remote-Sensing** (RS) and **Earth Observation** (EO) are often used in conjunction and even conflated. I believe a distinction is worthwhile because it allows us to understand the different perspectives brought by these two components, and to avoid misunderstandings.

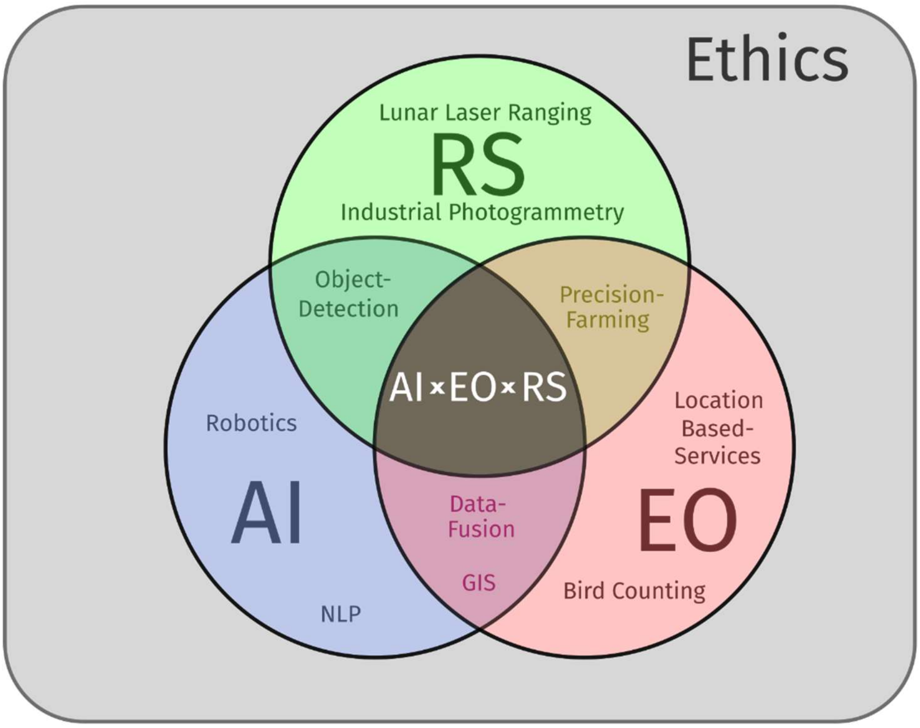

Figure 1: The scope of the essay is the area where the three components AI, RS and RO intersect. AI = Artificial Intelligence; RS = Remote Sensing; EO = Earth Observation; GIS = Geographical Information System, NLP = Natural Language Processing

The Chair of Remote Sensing (Chair of Remote Sensing, 2021) at which I study explains on its website: "*Remote sensing data mostly consists of digital pictures captured by active and passive sensors of earth observation satellites or aircrafts*." This already implies that EO is the main application of remote-sensing sensors and that those sensors are usually mounted on satellites or aircraft. What, then, is EO? As defined by the GEO, the Group on Earth Observations, it is a concept describing "*the gathering of information about planet Earth's physical, chemical and biological systems. It involves monitoring and assessing the status of, and changes in, the natural and man-made environment*" (GEO, 2021). By this definition it is, therefore, a very broad concept. The GEO lists possible applications, such as disaster resilience, mineral resource management, transport management, and food security. The GEO's definition of EO is close to my understanding of the field of Geography. Thus, a broad definition of EO would be the process of gathering and analysis of geographical data. This definition would also include the field of geodesy which is concerned with the size and shape of the earth and with the description of variations of its gravity field (Merriam-Webster, n.d.). Notably, the GEO definition includes other data-sources beside RS, such as data gathered by smartphones, water or soil samples or birdwatcher's notes on bird sightings.

This broad definition is not supported by the EU JRC's definition (EU Science Hub, 2016), which specifically refers to RS as the source of information: "*Earth observation is the gathering of information about planet Earth's physical, chemical and biological systems via remote sensing technologies, usually involving satellites carrying imaging devices.*"

That satellites or aircrafts are common platforms of RS sensors is supported by the USGS (USGS, n.d.) which defines RS as "*the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft).*" or the Merriam-Webster(Merriam-Webster, n.d.) which defines RS as "*the use of satellites to collect information about and take photographs of the Earth*" - Using these definitions, RS is a mere method used for EO. (Campbell and Wynne, 2011) compare further definitions of RS and find the common element to be "*The gathering of information at a distance*" but narrow the definition down to "*the practice of deriving information about the Earth's land and water surfaces using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the Earth's surface*." thereby also focusing on the application of RS to EO and explicitly not including "*meteorological or extraterrestrial remote sensing*".
From comparing these definitions, RS can be used in a narrow sense or a broad sense. In a narrow sense, which seems much more prevalent, it is regarded as a class of methods of gathering data for EO. In a broad sense, it includes any other gathering of information at a distance, such as the use of photogrammetry for automotive testing (Luhmann et al., 2006), Lunar Laser Ranging (Dickey et al., 1994), and assessment of silk patterns (Clermont et al., 2020).
RS and EO are therefore distinct domains with a close connection: RS is a class of methods which finds a common application in EO. In turn, a large part of EO data is collected via RS. That RS and EO are often conflated speaks to the significance of their relationship. While both concepts can be used broadly, there is a clear and important intersection between EO and RS, and it is this **intersection** that I will focus on in this essay.
For the purpose of this essay, I will use the term Remote-Sensing (RS) in its broad sense for the method of using satellite-borne, airborne, or terrestrial electromagnetic sensors to acquire data about objects at a distance and I will also use Earth-Observation (EO) in its broad sense for the application of gathering information about the earth's surface, for scientific, humanitarian, commercial or other purposes.
The third major component of AIxEOxRS is **Artificial Intelligence** (AI). It is both a field of cutting-edge research as well as an integral part of many current technologies. Nick Bostrom already noted in 2006 (CNN, 2006) that "*AI-inspired systems were already integral to many everyday technologies such as internet search engines, bank software for processing transactions and in medical diagnosis*." while also noting that "*A lot of cutting edge AI has filtered into general applications, often*

without being called AI because once something becomes useful enough and common enough it's not labelled AI anymore"- a phenomenon often referred to as the "AI Effect". Fifteen years later, I find that the term AI has lost its stigma as the technology is becoming both more powerful and more widely used. Great technical advances have been made using machine learning and in particular Deep Learning (DL). In RS, DL has quickly become the state of the art for a variety of operations such as automated object recognition, land cover classification and data fusion (Zhu et al., 2017).

Like RS and EO, AI is not a clearly defined concept. Practically all definitions (For a collection see Marsden, Paul, 2017) of AI presuppose a definition of the term intelligence.

Merriam Webster for instance defines AI as:

1. a branch of computer science dealing with the simulation of intelligent behavior in computers.
2. the capability of a machine to imitate intelligent human behavior.

What, then, qualifies as *intelligent*? It is common to define intelligence as the capability to learn and adapt to different situations and act rationally. This is true for all but the crudest mathematical computations which are intended to be used with varying inputs. An automated linear regression could be considered to be learning. Graphing-calculators, regularly used by children in mathematics classes, are capable of a large range of analytical and algebraic functions as well as games which respond to the user's input. From an EO perspective, geostatistical methods, automated projections, geoanalysis tools and many other functionalities implemented in GIS could be considered AI in a broad sense. Yet at the moment, the term AI is predominantly used for (and almost synonymous with) the field in which the most rapid developments are being made: Deep neural networks, most frequently built for and trained with a supervised learning method, using some form of big data.

In both the narrow and the broad sense, AI is an essential component of both RS and EO. In RS it aids with the processing of large amounts of data, which would be impossible for humans due to sheer volume. In EO it aids with the automated interpretation and information discovery within the varied EO data. In this essay, I will use the broad definition of the term AI to refer to any automated processing of data. But my focus will be the intersection between AI, RS, and EO, where geospatial data of the Earth (usually in the form of images) derived from satellite and airborne observations is processed or analysed using AI. Examples of AIxEOxRS are automated crop monitoring using drones, sea-ice monitoring, risk mapping of natural disasters, exploration of mineral resources, and the analysis of informal settlements, all using satellite or aerial imagery.

Due to the limits of my personal experience, I will focus on scientific projects and not commercial or humanitarian efforts.

Ethics

As defined by the Internet Encyclopedia of Philosophy (Fieser, James, n.d.), **Ethics** involves systematizing, defending, and recommending concepts of right and wrong behavior. Ethics can be categorized into three general subject areas, although they are interdependent and the lines between them are often blurry.

- **Metaethics** is the study of the origin and meaning of ethical concepts.
- **Normative Ethics** is the search for moral standards that regulate right and wrong conduct.
- **Applied Ethics** consists of the analysis of specific, controversial moral issues.

This essay focuses on Applied Ethics and will use the term Ethics to refer to this area of Ethics. Applied Ethics is not a field independent of other fields of science and technology. It is concerned with and realised by all human actions that have the potential to be controversial. It is, therefore, also part of RS, EO and AI. For example,

- there are ethical considerations in RS about scientific standards, access to data, and exchange of information,
- there are ethical considerations in EO about privacy and the permitted and justified uses of geospatial data,
- and there are ethical considerations in AI about algorithmic fairness and transparency.

In all fields there are ethical considerations about professional Ethics: the proper behaviour of professionals and their duties to their craft, their employers, colleagues, and society at large. Before the discussion of any specific literature or project, it is worth contemplating if Ethics within the scope of AIxEOxRS might be significantly **different** from Ethics in other fields of science, study, or commerce. An easy way to approach this is to examine whether the field itself is different. If it is not, then it is likely that many of the issues we face can be solved by adapting and combining solutions from other fields. If it is, then I may at least gain a prior notion about the ways in which it may require unique solutions, which in turn gives a useful focus for future work.

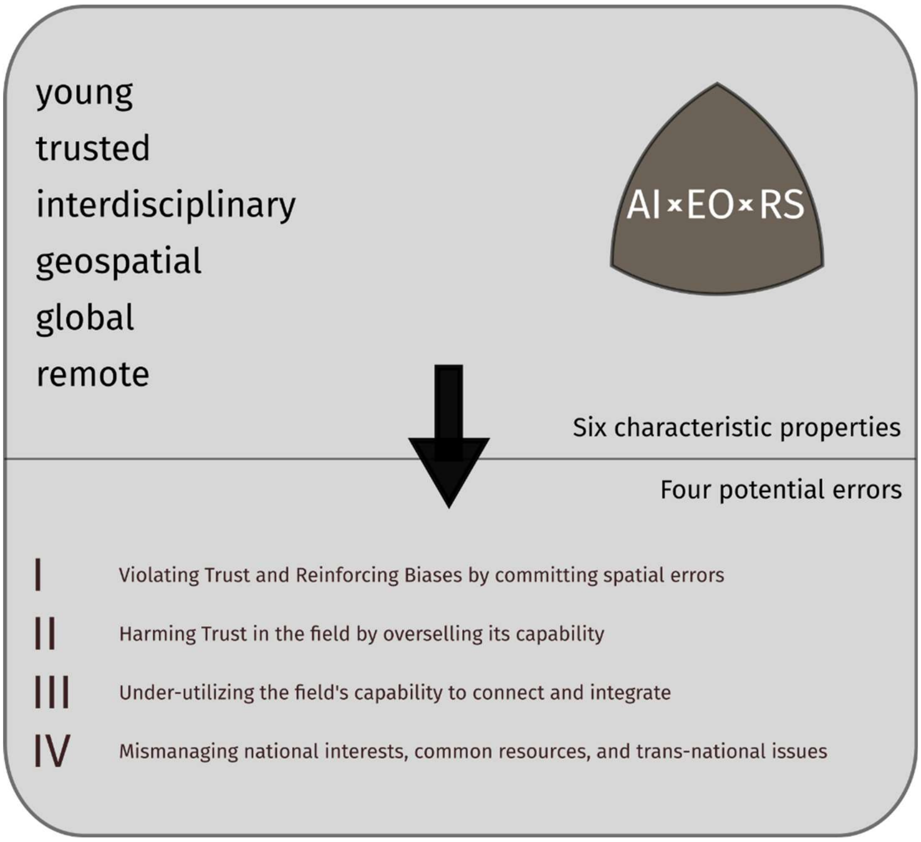

Figure 2: Properties of the domain that is the scope of this essay

Based on my own views and experiences, I identify six characteristic properties which distinguish AIxEOxRS from many, but not all, other fields of science and technology:

1. It is a **young** field experiencing a high rate of innovation - both within the three components, but also in the joint use of the three. Along with that goes increasing commercial maturity and a significant amount of media attention. To what extent this attention is justified, and which point of a *hype cycle* the field currently has reached, is difficult to tell. That is relevant in three ways: *Firstly, decisions made at this point could have long-lasting influence. Secondly, high rates of innovation put a high strain on the researchers and professionals to keep up with the latest developments. Thirdly, there is the risk of over-selling the capabilities of the technology.*
2. It is a relatively **trusted** field. Whether that is justified or not, the geoinformation derived from satellite imagery is often seen as objective, if not always perfectly accurate. Indeed, objectivity and freedom from bias is often brought forward as major strengths by proponents of RSxEO. AI algorithms themselves are often met with suspicion regarding transparency, accuracy, and benevolence. That does not appear to be the case for their use in EOxRS. In my experience, trust is especially strong for large-scale EO since the

low-resolution imagery which it typically uses is too coarse to make people feel their privacy is threatened. I hypothesize that in Germany it is often seen as following the tradition of Civil Engineering and Geodetic surveying which are known for producing highly precise measurements. The intuitiveness and power of a well-made map makes products derived from RSxEOxAI well suited for science communication, advocacy, and politics. *The field is receiving trust which makes it easier to gather public support.*

3. It is highly **interdisciplinary**. It is the norm rather than the exception to have teams consisting of people of diverse backgrounds. where people come together from engineering disciplines (Geodesy), computer science (Geoinformatics, Image processing), natural sciences (meteorology, geology, physical geography), social sciences (human geography, urban planning). Every discipline has domain-specific terminology, methods, and research focuses. That poses challenges (Blakemore, 2004) but also brings opportunities. *Firstly, there is a greater risk for communication issues. Secondly, there is a higher potential for exchange of concepts and diversity of ideas.*
4. It is implicitly **geospatial**. Many phenomena in the world are spatial. Via their spatial location, many phenomena can be linked. Databases on these phenomena can be linked and aggregated on spatial units. This indeed allows for the aforementioned interdisciplinarity, but is inherently problematic (Wetherholt and Rundquist, 2010). The division of the space in certain units, such as administrative units or pixels, is often taken for granted. However, the way in which spatial units are defined is usually linked to cultural conceptions and political or historical processes. Adding onto this, wrong choices in spatial units can lead to boundary effects, issues of scale, and MAUP (Weigand et al., 2019) with significant ethical implications. While those effects can be considered special cases of more general data issues, spatial data is particularly vulnerable due to the intuitiveness by which certain spatial organisations are often taken for granted. Geospatial data is particularly suited for visual presentation, but the making of maps can introduce biases by the mapmaker. *Political and historical conceptions of space may result in errors of scale and aggregation, which risk perpetuating and reinforcing unfair conceptions of and distributions within space. Cartographic visualisation can also be subject to biases.*
5. It is large scale and potentially **global** in scope. This amplifies the effect and often necessitates generalisations. Satellites both use a common resource (outer space) that is a common and they allow analyses that transcend national borders. It is likely that traditional methods of managing such technology on the level of nation-states will reach their limits. *Firstly, harms and benefits are amplified by the global scale. Secondly, globally applied methods may be overly generalized and not respect the diversity of the observed Earth. Thirdly, it can transcend national borders and it calls into question the validity of national borders and the exclusive sovereignty of nation states. Fourthly, it requires a common resource.*

6. Data gathering is, not inevitably, but often, **remote**. This allows the gathering of data without deep engagement with the observed phenomena and the context within which they occur. People in the observed area can have little knowledge of being observed and little choice and influence in the matter. At its worst, this enables surveillance. At its best, it unveils injustices in remote regions, like the scope of the deforestation in the Amazon rainforest, to a larger public. Further, as analyses are conducted from a distance, RS and EO tend to rely on proxy variables rather than measurements of the phenomena themselves. *Firstly, the nature of RS allows a detachedness (on the side of the analyst) towards the studied phenomena. Secondly, people in the observed area have less control over and engagement with the gathering and use of the data.*

None of these are **unique,** not by themselves. However, the combination of these properties creates a unique and intersectional space in which unique problems arise, and unique errors are possible. Four such errors may be:

I. Committing, due to excessive generalisation, excessive reliance on proxy variables or improper spatial techniques, errors which reinforce existing spatial biases, thereby violating the trust that the public places in the perceived objectivity and accuracy of the satellite data.
II. Over-selling, as a result of ambition and pride, the technical capability and objectivity of the methods, thereby harming the development of the field in the long term.
III. Under-utilizing, due to issues of communication and technical adaptation, the capability to integrate and connect very different domains, sectors and stakeholders and thereby actually contribute to a more nuanced and less biased view of the Earth.
IV. Mismanaging, as a result of lacking international cooperation and agreements, the trans-nationally shared resource of space and its potential to solve trans-national issues of Geography.

Such unique issues may require unique solutions, as it is less likely (although absolutely possible) that they are adequately addressed by solutions developed in and for other domains. An ethical code suitable for the field of AIxEOxRS should contain sufficient guidance to address these intersectional issues. More than that, I believe that it should focus on these issues.

Aim of the Essay

The intersection of the three components RS, EO and AI is where ethical issues from all three components add up and must be considered. I have further identified potential issues which are unique to this intersection and that cannot be disaggregated by its three components. The aim of this essay is to:

1. Identify the extent to which existing codes of Ethics
    a. can provide guidance toward general ethical behaviour in the space of AIxEOxRS,
    b. are compatible with each other,
    c. help to resolve the intersectional issues.
2. Identify those issues and ethical conflicts which appear in practical work and
    a. identify common elements and patterns,
    b. examine whether they can be resolved using existing codes of ethics.
3. Identify further issues that I have not considered.

To answer the first set of questions, I will review existing works on Ethics, one from each component of AIxEOxRS:

- Remote Sensing: ASPRS Code of Ethics
- Earth Observation: URISA GIS Code of Ethics
- Artificial Intelligence: EU Guidelines for trustworthy AI

To answer the second set of questions, I will review four studies which I have conducted as part of my master's studies:

- Reanalyzing GEDI Data for Detection of Ancient Maya Buildings
- Mapping Urban Villages using Fully Convolutional Neural Networks
- Modeling the Spatial Distribution of the Common Jogging Human
- VHR Segmentation of Agricultural Landscapes

To answer the third question, I perform a short literature review.

I explicitly intend to base this review on my own experiences and ideas as an academic novice. By design, this process will be clearly biased towards my own experiences and priorities. I make no claim to exhaustiveness.

In summary, the scope of this Essay is the Applied Ethics of EO using, among others, RS data and methods and methods of AI. The aim is to explore ethical issues within this scope.

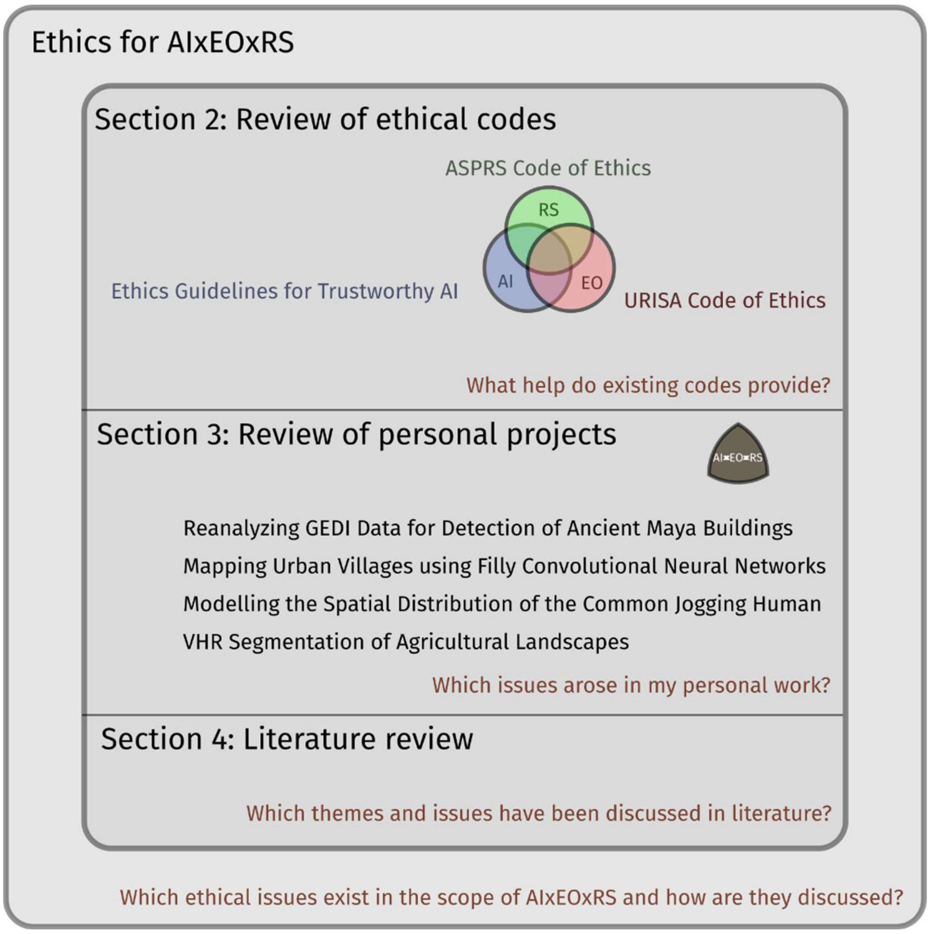

Figure 3: Structure of the essay

Structure of the Essay

The following sections are structured as follows: In Section 2 I review, for each of the three components RS, EO, and AI, one of the existing codes of Ethics. In Section 3 I review four different projects that I have been conducting as part of my master's program. In Section 4 I review additional literature connected to the issue. In Section 5, I summarize my findings.

2. Review of Ethical Codes

Existing Codes of Ethics

In this section, I review the ASPRS Code of Ethics and the URISA GIS Code of Ethics, two codes (Wetherholt and Rundquist, 2010) considered the best source of ethical information in the field. In addition, I review the EU Guidelines for Trustworthy AI. For all three documents I attempt to evaluate their focus, approach, and usefulness.

RS - ASPRS Code of Ethics

First agreements on the conduct of remote-sensing activities were made in 1986 in the form of *The Principles Relating to Remote Sensing of the Earth from Outer Space* (UNOOSA, 1986). On an international level, these outline which actions of RS are permitted and how issues between states are to be resolved. Notably, they prescribe international agreements and cooperation to maximize the benefit of RS technology. The principles are notable because they signify that the need for proper use of the technology was recognized early. They are, however, not a code of Ethics.

The necessity of having such a code was expressed a few years later by (Ciesla, 1991). Ciesla brought forward ethical considerations, and he particularly emphasized the importance of being aware of the limitations of satellite imagery. RS specialists must communicate limitations clearly to people who have no expert knowledge. Trust is built by consistent delivery of reliable information, whereas "*Overextending the capabilities of a technology will only serve to discredit it when it is discovered that the end product does not represent the conditions on the ground*". This is true for all technology but more so for satellite-based RS, which indeed has the potential for greater objectivity and trustworthiness. To preserve this trust, Ciesla warns against the temptation to oversell a new technology out of euphoria or a chance to earn reputation or profit and does so in no uncertain terms: "*even 'garbage' can be packaged to appear to be an accurate, reliable product* ".

Despite these relatively early foundations, actual codifications of ethical practices seem rare even today. The best example of a true code of Ethics for RS is the one of the American Society for Photogrammetry and Remote Sensing (ASPRS) from 2002 (Blakemore, 2004). While some other organizations exist, like the International Society for Photogrammetry and Remote Sensing (ISPRS), none of these appear to have adopted any relevant ethical codes. The ASPRS code is short, containing only 7 principles that outline the desired professional conduct with regards to competition, interactions with employers, all clients, colleagues and associates, and society at large. In addition, general respect for privacy as well as legal and ethical interests of others is required by the 7th principle. Clearly, the goal of this code is to strengthen trust in the profession.

The code is explicitly founded on a moral philosophy based on honesty, justice, and courtesy. Its principles are supposed to be "*a way of life rather than merely for passive observance*". Therefore, I believe it can be considered to be in the tradition of virtue Ethics. Due to the breadth of applications in which RS technology may be deployed, this may be the only way in which an encompassing code can be created.

However, as a result, the code is very general and does not provide any specific examples of concrete ethical actions which are desirable. Further, it appears to presuppose that the standards of proper behavior are already established. As an example, the code condemns the exercise of "*undue influence*". What qualifies as *undue* is left to the interpretation of the reader.

While an experienced professional with lots of interaction in the field might have some intuitive understanding of *dueness*, a novice would find no help at all in this line. In a way, the ASPRS code only names dimensions (in this case *dueness*) along which ethical behavior might be evaluated. It does not explain these dimensions further or provide any points of orientation along those dimensions. Neither does it consider ways in which these dimensions affect each other.

Further, the code does not acknowledge the possibility of conflicts of interests, which are likely to arise from the professional's position between employer, all clients, colleagues and associates, and society at large. I find it worth noting that the URISA code, discussed in the next section, does acknowledge such conflicts.

In my opinion, the code is agreeable, but not practically useful. It offers a list of ethically relevant dimensions to consider, but no guidance on how specific judgements ought to be made and how dilemmas should be resolved. In practice, I expect it will offer little improvement over the application of intuition and common sense. Especially for novices with little experience to fall back on that limits its use. However, the code's reliance on very widely accepted principles makes it more likely that it will be acceptable to people of different backgrounds. and the generic phrasings make it less likely that the code will become obsolete due to technical development. As a result, it can serve to establish a basis for discussion.

EO - URISA GIS Code of Ethics

In EO, ethical issues have been discussed more widely, especially under the label of GIS (See section 4 for a brief discussion of the literature). The origins of a professional code for GIS practitioners can be found in 1993, when Craig wrote that the GIS profession was in need of a code of Ethics. He acknowledged that creating one was a daunting task, due to the multidisciplinary nature of GIS. He recommended that a new code of Ethics should build on the Ethics work of other professional organizations.

Ten years later, in 2003, the Urban and Regional Information Systems Association (URISA) adopted a code of Ethics which has also come to be used by the GIS certification institute (GISCI, 2021). This code, like the ASPRS code, is a code of professional Ethics, intended to preserve and enhance public trust in the discipline. But more than that, it was intended to be a starting point for the ethical work of URISA members. As Craig, head of the task force, explains in the publication statement:" It's *not that we expect the Code will be a front-line of defense against wrong-doing. Instead, the Code provides a touchstone for members to identify and resolve ethical dilemmas that they encounter in their work."*

The core of the code, formulated in a positive tone, are ten obligations. The obligations are clearly structured into obligations towards *Society*, *Employers and*

Funders, *Colleagues and the Profession*, and towards *Individuals in the Society*. As the term "obligations" suggests, the code follows the traditions of deontological Ethics.
A bibliography accompanies the code and provides background information which is helpful for understanding the frame in which the code is set. A statement accompanying the code explains its philosophy and presents a few guidelines that are supposed to be unique to the GIS profession. These relate mostly to the data policy, and -despite the claim of uniqueness- I see them as addressing general data issues, with no particular spatial components.
As I stated before, the code is in fact practically used and discussed by URISA and the GISCI. Despite that, (Verrax, 2016) argues that the code offers little help for professionals facing a dilemma. For instance, she finds that the goal of confidentiality conflicts with the goal of privacy, and the code offers no help in resolving the dilemma. I think that since the creators of the code intended for it to be a "*touchstone*" and nothing more, that might be by design. Providing specific guidance is not the ambition of the code's creators, who delegate that duty to the community and to existing works in literature. Indeed, the code recommends that when faced with a dilemma "*Help might come from talking with colleagues or reading relevant works* ". The code recommends contemplating Virtue Ethics, Utilitarianism, Kantianism, and Deontology in an approach suggested by Kidder, (1995). I believe that is no realistic solution for any individual professional, especially a novice facing a dilemma. Not only will they be overwhelmed by the prospect of studying four branches of normative Ethics to resolve a practical issue. The four theories are also different enough that they might lead to very different conclusions on the matter at hand, leading to a form of *Analysis Paralysis*. I therefore must agree with Verrax when she finds that *"the given recommendations are so general that the very educational part does not seem fully fulfilled*".
Verrax further criticizes that the code foresees no penalty for infringement. This is especially surprising considering Craig's feeling that "*the GIS community should enforce its code of ethics*" (Craig, 1993).
An example of the code being practically applied to a dilemma is found in a 2020 issue of the *GIS Professional*, an URISA newsletter, where the author (Salling, 2020) discusses the actions of a GIS professional who was fired after allegedly refusing to change data on a COVID-19 dashboard web site in Florida. The author acknowledges that there was conflict between the professional's obligations to society and her obligations to her employer. The URISA board of directors stated on this matter that the professional followed the code of Ethics in this dilemma, and that "*What is important is to strive to do the right thing*" - A nod to Kant's idea of the importance of the *Good Will* (Kant, 1785)? Perhaps someone following a different ethical theory approach would have come to a different judgement here. This shows that judgements cannot be made using this code. It is too broad to provide practical help on any specific issue.

In conclusion, the code is clearly a code of professional Ethics in the deontological tradition. It focuses primarily on the Ethics of data and on the relationship between the GIS professional and different involved parties. In my opinion this code does a good job in formulating its goals but does nothing to help resolve dilemmas when they arise. The counsel to seek the ethical course of action in discourse with colleagues is a good one. Especially in an interdisciplinary field, the experience from specialized colleagues can be a great benefit. However, I believe that such discourse should also include a variety of stakeholders. Otherwise, such discourse may perpetuate existing biases.

AI - EU Guidelines for trustworthy AI

In the field of AI, a far reaching discourse on Ethics is ongoing, and a number of ethical guidelines have been released in recent years (see Hagendorff, 2020 for a review of 22 major ethical guidelines). Jobin et al., (2019) identifies that among 84 documents on AI Ethics, most of them are produced by private companies and governmental agencies. One of these documents is the Ethics Guidelines for Trustworthy Artificial Intelligence (AIG), presented in April 2019 by the High-Level Expert Group on AI. The stated aim of the AIG is to promote trustworthy AI, which is defined to be lawful, ethical, and robust. They further aim to offer guidance on how the latter two can be realized. Unlike the codes of Ethics of the ASPRS and URISA, the AIG are not a code of professional Ethics. This is reflected in their larger audience and scope. They are explicitly addressed towards all stakeholders in matters of AI. In the current day and age, that is likely most of the world’s population.

At the heart of the AIG are four ethical principles with seven key requirements. The document goes into detail on how each of the requirements is necessary, what harm it is supposed to prevent, and what benefits its realization brings. On how these requirements can be implemented, the guideline describes both technical and non-technical methods.

Further, it provides an assessment list which can be used to evaluate an AI system’s conformity with the guidelines. This list is explicitly stated to be non-exhaustive. The AIG provides detail on how this assessment list can be integrated in the governance structure of an organization, and how assessment of AI can be realized in general.

The lists are longer than the ASPRS or URISA codes, but they are still generic. The AIG recommend that they should be tailored to specific contexts and use-cases. Yet they also caution that even the most fine-grained, domain-specific code can never be sufficient. Rather they advise that ethical culture and an ethical mind-set be built and maintained, both within the community at large but also within organizations.

That the AIG assign certain ethical roles to the members and groups within an organization is something I find particularly valuable. By making roles and duties explicit, accountability is improved. But more than that, clear assignment of roles can be a great help for the individuals involved, especially if their place within the structure of the organization is otherwise uncertain. That is more likely to be the case for inexperienced or new employees and novices in general. However, there is a danger that the assignment of roles might also come with a narrow focus of the individuals involved and facilitate a box-ticking mentality. Regular exchange between the different roles is therefore all the more important, especially when conflicts occur. Therefore, I particularly agree with the advice to log all results both in technical terms and in management terms. In an academic context, the boundaries in communication might not be so much horizontal, but rather vertical - scientists from different backgrounds using different jargon. Making some effort to use mutually intelligible terminology is, in my opinion, justified, even if some precision is lost.

The importance of facilitating communication is further highlighted by the AIG's advice that hiring from diverse backgrounds should be encouraged- not just as an end in itself but also as a means to provide more diverse perspectives, gain additional creativity in the innovation of technical solutions, and find third solutions out of false dilemmas.

The guidelines acknowledge that tensions and dilemmas between the stated ethical principles exist and advise that these should be dealt with via accountable deliberation. Trade-offs should be addressed in a rational and methodological manner within the state of the art. In this way, the guidelines favor systematicity over intuition while recognizing the limits of systematic and fixed guidelines.

The acknowledgement of possible trade-offs can, in my view, be seen as a sign of allowing a degree of utilitarianism. However, the AIG also include views that are clearly deontological, and they follow explicitly a fundamental rights-based approach. They acknowledge, for instance, certain boundaries that should never be crossed, such as those given by fundamental human rights, which are never supposed to be subject to any trade-offs. As well, they include a few absolute prohibitions such as "*AI Systems should not represent themselves as humans to users*". That the AIG recommend exchange and discourse as solutions to ethical dilemmas can be seen as support for discourse Ethics. As a result, I can not clearly place it in one of the typical theories of normative Ethics.

The AIG are far more extensive than the narrow code of Ethics by the ASPRS and URISA. With a broad scope, they cover many aspects that are relevant to AIxEOxRS and many of their principles can be adopted to pure RS and EO as well. As they do not just provide the requirements, but also details on why they were chosen and how they could be implemented, the document is also far longer. That length may make them less approachable, but I find them highly readable. The assessment list, while general, serves as a reminder of potential issues to consider. I believe the list succeeds in being broadly applicable. That any such application necessitates further additions or changes to the lists is clear. Sadly, this puts further requirements towards the AIxEOxRS community or the individual practitioner, who is expected to engage with the underlying ethical ideals as well as find concrete ways to fulfill the requirements. Such efforts, however, will not go to waste and likely become easier as domain-specific codes are developed. This is partly because people will become more accustomed to the process, but also because they will have a greater body of work to draw upon. To get this process started, the AIG serve to establish a common ground and to be a source of inspiration. When it comes to the application of AI to EO and RS, the AIG provide a pool of ideas that are, to my knowledge, not yet common practice even in AI. Examples of these are standardization of AI systems, red-teaming, and bug-bounties. Technical solutions, such as explainable AI (XAI) have received significant attention in the field of AI (Barredo Arrieta et al., 2020). Here, it is up to the RS and EO community to closely follow the rapid development in other fields and try to adapt solutions.

In conclusion, the AIG provide a set of core ideas, requirements towards AI, but also guidance on how to realize and assess solutions. They acknowledge that dilemmas can occur and suggest they be solved via educated discussion under consideration of fundamental requirements. Thus, they strike a balance between discourse and deontological Ethics. For me, as a novice, they provide inspiration, ideas, and ideals.

Comparison

The ASPRS and URISA codes are concise and general codes of professional Ethics while the AI guidelines are laying out an entire framework. This must be considered when they are compared. Nevertheless, I believe there are certain differences and commonalities that are worth pointing out:

Firstly, while all three lay out ethical conduct, they are **different** in their scope. The URISA and ASPRS codes are of professional Ethics and state common principles of a group (the profession) and how these manifest for a member of this group. Contrary to that, the AI guidelines are a code of Ethics concerning the use of an entire technology and field of science. They are not targeted towards a specific group but rather any group or individual who has a stake in the use of the technology. *Secondly*, the professional codes focus on proper conduct of individuals in their role as professionals. The AI guidelines, on the other hand, focus on proper use, development, and governance of a technology, and are not addressed to personal behavior as much. *Thirdly*, an obvious difference can be found in the length, format, and detail: The URISA (5 pages) and ASPRS (1 page) documents are far shorter and less detailed than the AI guidelines (41 pages). Where the former two are lists with just brief introductory statements, the latter contains sections of flowing text in addition to its lists. At the cost of conciseness, this increases the content it supplies and therefore the help it can provide to a reader looking for guidance in ethical matters. Broadly, I find that the two professional codes are more successful in guiding the reader's attention towards certain issues. However, they offer no help in resolving them. I find that this is exemplified by the use of the word *undue* in the following two examples:

- "*Avoid undue intrusions into the lives of individuals*." [URISA]
- "*Exercising undue influence or pressure, or soliciting favors through offering monetary inducements*" [ASPRS]

The judgement of what is "*due*" in these cases is left to the reader. Compare this to one example of the AIG which, on the topic of privacy protection, are more specific about its scope as well as prohibited uses, namely anything that allows for discrimination: *"[Subject to privacy and data protection are] the information initially provided by the user, as well as the information generated about the user over the course of their interaction with the system [...] it must be ensured that data collected about them will not be used to unlawfully or unfairly discriminate against them".*

Now it must be said that much of this difference is by design: The URISA code explicitly avoids the listing of specific unethical actions: "*The problems with listing acts to be avoided are: 1) there are usually reasonable exceptions to any avoidance rule and 2) there is implicit approval of any act not on the list"*. And while this sentiment is shared by the AI guidelines- which emphasize that the lists included in the document are non exhaustive and should always only be tailored to more specific domains and applications- they are, by far, the most extensive of the three reviewed resources. Besides just stating their principles and requirements, they inform on how and why those are relevant. Further, they name concrete technical and non-technical solutions and thereby provide guidance. Further still, they provide an assessment list which can form the basis of ethical review of technology. This greater specificity means that they need to be regularly updated to remain relevant. It also makes them the most useful, but only under two conditions: The reader having some knowledge about the AI domain and the ability to consult this much larger document. The two professional codes have lesser requirements. A *fourth* and final difference can be found in the ethical traditions of the codes. The URISA code is explicitly deontological. I see the ASPRS code as an example of virtue Ethics founded on the virtues of honesty, justice, and courtesy. The AI guidelines combine elements of deontology and discourse Ethics with certain utilitarian aspects (e.g., to "maximize the benefits of AI systems while at the same time preventing and minimizing their risks."). Interestingly, this is counter to the argument by Harris (2013) that the most common implicit ethical code for Earth observation satellite data is utilitarianism.

Despite those differences, **commonalities** exist as well: All three of the reviewed codes make mention of the issue of privacy. All three mention that beside one's immediate partners, one should consider society at large. As well, all three state one of their goals to be the enhancement of trust and trustworthiness in the disciplines and technology. Besides that, content wise, there are numerous overlaps between two of the three codes. For example, both ASPRS and URISA state that one should only accept tasks for which one is qualified. A final commonality is that

none of the three documents include any sanctions. Only the AI guidelines make suggestions about AI assessment and governance.
In conclusion, the ASPRS and URISA documents are examples of professional codes of Ethics for their specific fields. By contrast, the AI guidelines are more general and more detailed. As a result, the former two documents are much shorter and quicker to read, while the latter provides greater help.

Discussion

Can the codes provide guidance toward general ethical behavior in the space of AIxEOxRS?
The professional codes of ASPRS and URISA on their own are similar to the codes of other professions (I find that the ASPRS code in particular could be applied to many unrelated professions). All of the principles they state, without exception, are applicable to the spaces of AI, EO, and RS. That is not the case for the AI guidelines. For instance, the AIG address certain issues of privacy, explainability and algorithmic fairness which arise from automated classification and decision-making affecting peoples lives directly. For a purely RS professional, who does not work with individual level data and does not work with automated decision making, such issues would have little relevance. These issues would be relevant to somebody working in AIxEOxRS however, who is likely to engage in joining data and modeling of processes of which human individuals are an important part. Such a professional would benefit from considering the AI guidelines.
I believe that in their own way, all three reviewed codes have some benefit to the AIxEOxRS space:
The approach of the ASPRS, grounded in virtue Ethics, could serve to create an environment in which the pursuit of comprehensible, common ideals leads to professionals taking pride in ethical behavior and discussion. Its generic formulation means it will not become obsolete due to technological developments.
The deontological approach of the URISA poses high requirements to ethical behavior but offers little aid in realizing them. Yet, it recognizes its limitations and encourages discussion. Its benefit lies in stating ideals and leaving open the ways in which they are reached. From that comes its benefit: It firmly fixes certain core obligations which the community can use as orientation for discussions but allows freedom in how the community practically fulfills these obligations.
The AIHLEG can serve as a source of inspiration - both for discussion or underlying principles and concrete implementations. It provides an adaptable framework which can be the seed for more concrete domain-specific ethical codes and systems.
Are the codes compatible with each other?

Is it then optimal to consider all three documents? If the three were very different in their ideals, that would not be possible. However, I find no principles in any code that are directly contradicting principles of another code. Yet, issues can always arise when certain goals are competing for resources. That is possible within a certain code, but more likely across them, simple because more principles must be considered. As an example, in addition to the already extensive AI guidelines, the two professional codes put forward the principle of continued learning and self-improvement. While it is hard to argue that self-improvement would be a bad thing for someone working on AI, it does take time and effort. These are valuable resources that could obviously also be used to work on the realization of other principles. Solving such issues of resource allocation becomes more difficult as additional goals are introduced. Only within a consequentialist ethical framework with a shared concept of utility, the codes could be reconciled. That, however, cannot easily be created, because the codes are based on different theories of normative Ethics. Combining them would require significant (re-)consideration of their underlying principles - possible, but unrealistic. In practice, conflicts would be better resolved on a per-case basis rather than with a complete shakeup of the underlying normative Ethics.

In conclusion, I believe that the three documents can be considered jointly and are not inherently contradictory. This joint use means that goal conflicts and dilemmas are more likely to arise and more complicated to resolve.

Do the codes help to resolve the intersectional issues in particular?

In the Introduction, I identified four potential intersectional issues. To what extent do the three codes address them, and, ideally, resolve them?

I - Violating trust in the field and reinforcing biases by committing spatial errors

The AIG, explicitly intended to foster trust, cautions against unfair biases. The issue is addressed, and all its recommendations apply to spatial data, although they are general. In this regard, adapting this to the particular errors and biases occurring in the spatial domain is an open task, which would be left to the spatial community. This is acknowledged by the AIG.

The code of URISA is also rather general on matters of bias and fairness. It encourages "*to treat all individuals equally, without regard to race, gender, or other personal characteristic not related to the task at hand*". Specific threats to equality, or reasons why the task at hand may require equality to be threatened are unfortunately not specified. This is particularly disappointing since the code does make specific recommendation on other matters, such as autonomy and privacy,

The potential that spatial errors and biases can negatively affect fairness is not acknowledged by ASPRS, except possibly in the broadest possible way (via the requirement to "*Recognize the [...] ethical interests of others*").

II - Violating trust in the field by overselling its capability

The danger of exaggerating the capability and reliability of the technology and thereby harming the field in the long term is directly addressed by the URISA: "*Admit when a mistake has been*

made and make corrections where possible ", "Be forthcoming about any limitations of data, software, assumptions, methods, and analysis". It is also implicitly addressed by the ASPRS codes points to "*Undertake only such assignments in the use of mapping sciences for which one is qualified by education, training, and experience" and* to refrain *from "Advertising in a self-laudatory manner*".
The AI guidelines make no explicit mention of this issue. They require transparency, which, if implemented to match high standards, would allow outsiders to accurately judge the capability of the system, but only if those outsiders possess the required knowledge and time. They further require assessment and reporting of negative impacts. They way this is described suggests a monitoring not just at the release of a method or the launch of a system but rather during its entire lifetime. I think this would be particularly valuable when the capabilities of a system are not perfectly known from the beginning, but a release is nevertheless desirable. Such monitoring may foster trust and goodwill from stakeholders.

III - Underutilizing the capability to connect and integrate

As stated before, a potential strength of AIxEOxRS is to overcome biases by including stakeholders and scientists from different fields in design and decision making. Recognizing this, the URISA encourages to "*Strive for broad citizen involvement in problem definition, data identification, analysis, and decision-making*". while one of the core requirements of the AIG is *diversity, non-discrimination and fairness*. The value of diversity is directly acknowledged, inclusion of stakeholders in decision making is recommended. Therefore, this issue is addressed adequately by those two codes. The ASPRS recognizes the value of interdisciplinarity and public involvement by recommending "*Interchange of information and experience with other persons interested in and using a mapping science, with other professions, students and the public*". Limiting to a mere exchange of information without inclusion in decision is less ambitious than the other two codes, but it is a start.

IV – Mis-managing national interests, common resources, and trans-national issues

The ASPRS and URISA codes have a focus on professional behavior, and international matters are out of their scope. This is regrettable, but, considering their audience, understandable. The AIG, however, recognize that the impact of AI systems does not stop at national borders and encourage international consensus building.
I am sure this is doubly necessary when spatial topics (EO) and spatial technology (satellite-based RS) are involved because it is not just the impact of AI that is trans-national - to some extent, it is trans-national by its very nature. Satellite technology simply requires the use of orbits around the Earth, which are becoming increasingly cluttered by satellites and space debris. The danger this poses to the shared resource one that can only be managed through international cooperation. Regulations may or may not be passed in time. Until then, we should not rely on purely technical solutions, but discuss how an acceptable solution might look like – which values are important and where conflicts of interest can already be identified. This difficult work may eventually be left to politicians and legal experts. But I believe that the

practical insights of AIxEOxRS professionals, who occupy key positions in the value chain, can be a valuable addition to this process.

In conclusion, no single code fully addresses all intersectional points. However, someone considering all of the codes would be guided to at least concern themself with the intersectional issues. Mostly lacking is the attention towards potential international issues, which is perhaps understandable considering these are likely unsolvable by AIxEOxRS community, but regrettable as they are still worthy of consideration. Unfortunately, when it comes to finding solutions to specific issues, the practical help the codes provide is limited. Transferring the principles towards the AIxEOxRS domain, identifying domain-specific manifestations of issues, and finding concrete solutions to these issues is necessary if the community wants to do more than pay lip service to the ethical principles on which the codes are based. That, however, will require work and willingness to have uncomfortable, inquisitive conversations about work and practices. By the AIxEOxRS community, organizations, or the individual professionals. I believe that these efforts would be justified by the presence of these issues in the codes. More than that, I believe that this would be an effective starting point for adopting the codes to the AIxEOxRS domain.

But who should take charge of this adaptation? Who should be involved in creating a domain-specific code? Should it be down to existing organizations, the broad community, or a select council of experts?

Technical expertise and experience are almost required to make educated decisions involving three distinct domains. Experience in the politics and the modus operandi of the field would be desirable as well. This means that a technocratic approach may be favored, in which a relatively small council of experts identifies ethically desirable principles and goals and develops and adopts solutions to reach them. The choice of these experts would be an important decision in itself. The 52-member High-Level Expert Group on Artificial Intelligence (HLEG AI), who created the AIG, had a definite skew towards representatives of industry. According to HLEG-Member Metzinger (2019) this led to vague and lukewarm guidelines without any clear red lines.

Democratic approaches sourcing from a larger community, the obvious alternative, create difficulties in the technical realization of the decision-making process. Minority views may be underrepresented. However, democratic approaches may have the merit of inherently furthering ethical goals like accountability and stakeholder engagement. In a technocratic approach, I believe, accountability, transparency and participation are (likely by design) more difficult to realize.

I think it is possible and plausible that a mixed model is the best solution. In finding it, both political theory and the practical examples of other domains can serve as examples.

If it turns out that only a few organizations are willing or able to devote their attention to ethical issues, some sort of ethical oligarchy or even autocracy might develop. This, I suspect, would likely result in biased outcomes and those would be thoroughly undesirable. I do not find it difficult to believe that large companies like Facebook or Google, already at the forefront of technical development, would like to claim dominance in ethical development as well. They certainly have reason and resources to do so. Whether they can realize this will in large part come down to public acceptance and competition. And, of course, whether they will themselves hold to the ethical guidelines they create, or use them as superficial tools for *"Ethics-washing"* (Benkler, 2019). Whatever the process turns out to be, whether it will be technocratic, oligarchic, or democratic, it should be accompanied by a public debate. The ideals at the core of the three codes, and their underlying values, agree on this.

3. Review of Personal Projects

Over the course of my studies, I performed several study projects in the AIxEOxRS space. Despite their small scale, they can still serve to identify issues that a novice in the field faces. For each project, I provide a short summary and a discussion of ethical issues which I identified upon reflection.

Projects

Analyzing GEDI for Archaeological Applications

Project Summary

In this project (Kokalj and Mast, 2021), we analyzed the applicability of airborne laser scanning (ALS) data from the ISS-borne GEDI Mission for applications in Archaeology. This data is publicly and freely available, in contrast to the difficulty and expense of airborne surveys. We were interested in whether the resolution of the data is sufficient to detect remains of Maya cities on the Yucatan peninsula in Mexico, a task for which ALS surveys are commonly used. At the beginning of the project, few tools were available for data acquisition, analysis, and visualization, requiring me to write my own code for the processing of the data. Over time, dedicated Python and R packages were made openly available which surpassed my code in utility.

The results of our study were clearly negative, which we deemed relevant for publication. As part of the publishing process, I prepared my code for open access. In doing so, I noticed a mismatch between one analysis method we used and its description in the text (which claimed that the analysis method was different and more expressive than it actually was). Recognizing this error, we revised the analysis method to reflect the description and our actual goals more accurately before we proceeded with the publication. The changes made the results more ambiguous but also more interesting. We cleaned the code and the data of geoinformation and published them on GitHub for the purpose of allowing reproducibility of the study, with the recommendation that further studies use the more accessible dedicated packages that had been developed. Funding from the project was used to allow open-access publication of the article itself.

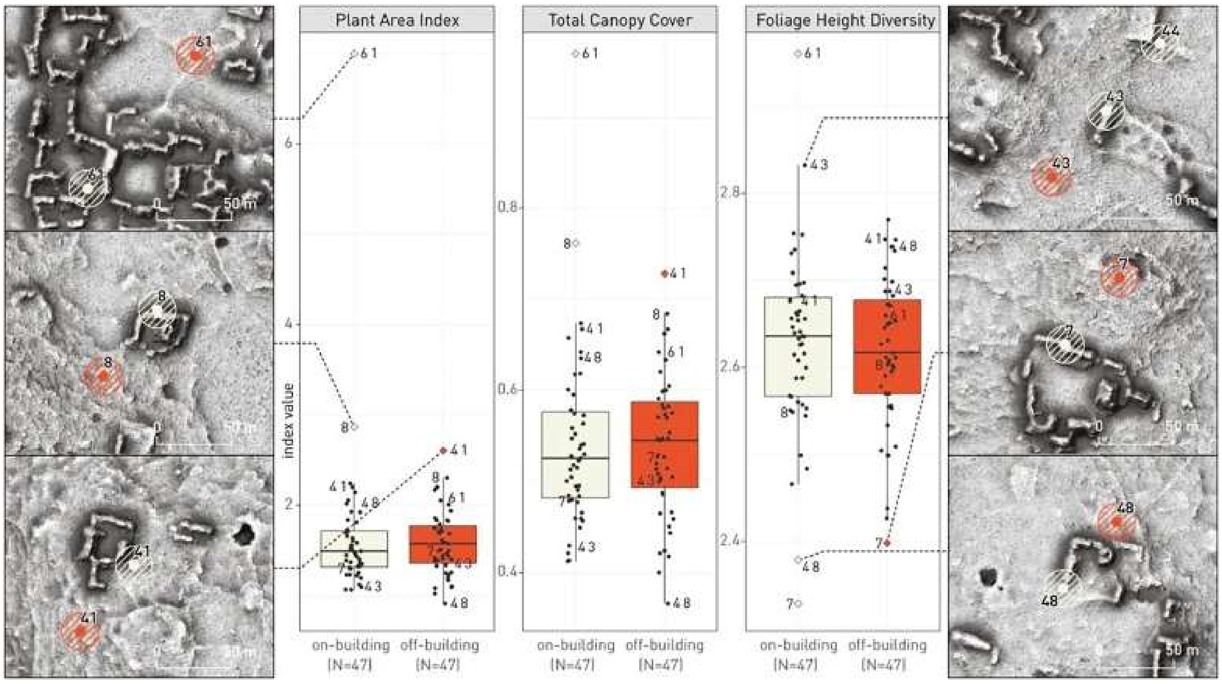

Figure 4:Comparison of on-building and off-building LIDAR footprints in Chactún, Mexico. The values in the chart are biophysical indices. No clear difference can be seen. Kokalj & Mast 2021.

Discussion of the Project

In this project, accountability and transparency are achieved by publicizing not just the article itself but also the data and the code that was used to generate the paper's results. This step also led to me finding an error and improving the overall quality of the research greatly. Publicizing the data, however, also can lead to negative outcomes: It reveals the location of archaeological sites, which might become victims of looting as a result, thus creating a negative impact on societal and environmental well-being. To protect the sites, we implemented an intermediate solution: We stripped the data of explicit geoinformation, meaning that the location of the sites could no longer directly be identified. However, anyone with basic knowledge of the data and method would be able to find ways to infer the locations even from the protected dataset. This measure, thus, affords a modicum of protection, but not more. Is this an acceptable compromise?

The SAA Ethics in Professional Archaeology states as one of their principles, *Public Reporting and Publication*, that knowledge gained must be presented to the public "*within a reasonable time*". However, "*An interest in preserving and protecting in situ archaeological sites must be taken into account when publishing and distributing information about their nature and location*". The SAA

Ethics acknowledge the conflict with their principle of *Stewardship* which states that the preservation of the archaeological record is the responsibility of all archaeologists. For a detailed discussion of the Ethics of RS in Archaeology, I refer to (Fernandez-Diaz et al., 2018). A blanket solution, it seems, is not practical, and archaeologists are expected to rely on their experience in evaluating potential outcomes and exercise common sense in their judgment. In the case of our study I am confident that the experience of my supervisor qualifies him to make this judgment.

Yet not all ethical actions required confronting dilemmas, as two examples from this project also show: Firstly, we made the article openly available. The requirement for sharing results with the public (posed by the AIG and the URISA) could be met solely by the commitment of financial resources, which, within this project, were available. I am particularly happy that publication was possible despite generally negative results, and we therefore avoided contributing to publication bias. Secondly, I admitted and corrected a mistake I made, thus fulfilling a requirement of the URISA code. While unpleasant, it required no resources, and any consequences were only positive.

Mapping Urban Villages using Convolutional Neural Networks

Project Summary

In this project I explored the feasibility of using a particular type of neural network for the detection of Urban Villages (UVs) in China (Mast et al., 2020). UVs are a type of informal settlement resulting from China's land use system. I had never been to China, much less an UV, but a Chinese research associate of the institute had gotten me interested in the topic.

A literature review revealed that examination of UVs using RS had been rare compared to other types of informal settlements such as slums and favelas. It is likely, however, that I was missing out on a large body of Chinese literature.

Despite my lack of understanding of Chinese cities I collected training data of UVs in the highly urbanized areas of the cities of Shenzhen and Dongguan. This was done by visual inspection of temporally heterogeneous aerial imagery (Google Earth), aided by outdated maps I found in prior publications. I also collected such data for the more rural northeastern part of Shenzhen, with the intention that this data be used for testing the final model. UVs are a socioeconomic or political item that is often, but not always, co-occurring with a certain morphological type. I was only able to map this morphological type and not the UVs itself, and, lacking a true reference, was unable to validate to what extent the mapped objects match the socioeconomic and political UVs. The results were generally positive. The model was able to detect UVs in the training region with high statistical accuracy (as validated by the manually collected validation data), but the accuracy suffered in the testing in the rural region, where UVs often look differently and are found in different spatial contexts. This makes the transfer of information (Wurm et al., 2019) challenging for

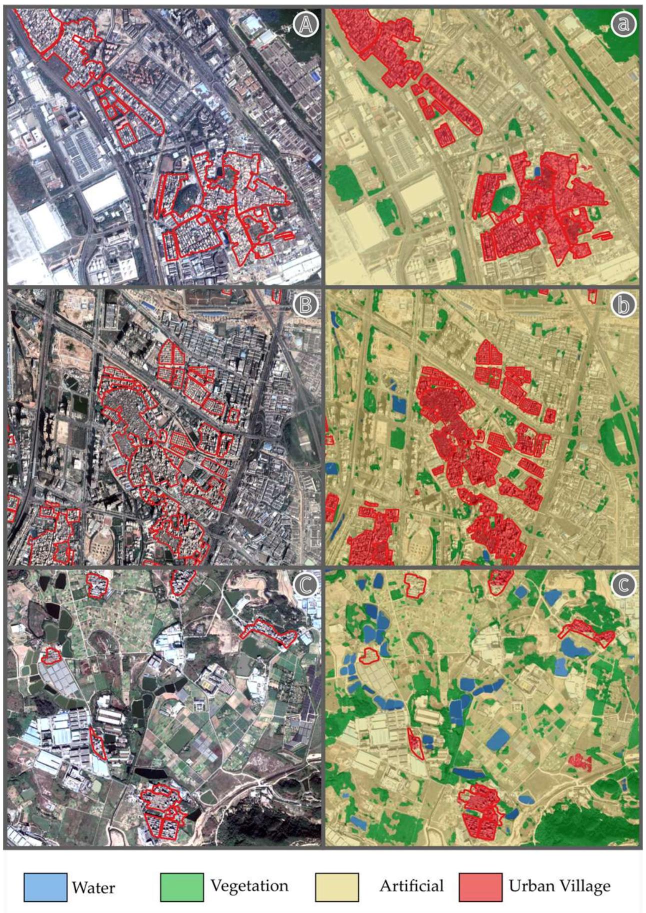

Figure 5: Results of the mapping of Urban Villages (UVs) in Mast (2020). Left is the validation data, right is the prediction of the algorithm. Basemap: Google Earth

humans as well as AI models. The accuracy was high enough to roughly outline the shape of the UVs. The created data was not used for further analysis. Besides minor tuning, the model was used as a black box and the inner workings of the network were not explored due to a lack of technical understanding on my part. Instead, I inspected the results visually to check for any systematic errors or patterns.

The results were published, the data and the model were not made available due to their large size. I recommended in the publication that research about the UV phenomenon should be given a high priority for its sheer magnitude, without making any further recommendation about the political or social implications of the results or the study or the existence of the UVs themselves.

Discussion of the Project

The openness of RS data allowed me to study an urban phenomenon that I had little connection to and experience with. Had I more knowledge of the study area and the UV phenomenon, I could have collected more accurate training data. Technical robustness, accuracy and reliability would have increased as a result. Had I more information of the socioeconomic and political situation, I could have taken efforts to correct for systemic biases and unfairness. Of course, it is not the case that openness inevitably led to decreased accuracy and unfairness. Even with the use of open RS data I still could have conducted ground surveys. Data collected in such a manner is desirable for many reasons. Unfortunately, surveys are expensive, and such expenses must be justified. In my case, I see no way a survey could have been possible. Hiring additional help for the labeling process is also expensive and introduces additional complexities. A full discussion of biases in labeling is far beyond the scope of this essay, but a simple conclusion of my experiences is this: Labeled data of high quality requires expert attention and high expenses in time and labor. The expectation of perfect data is unrealistic in most situations, but with greater financial resources, better data can often be acquired.

In a similar vein, the public Google Earth data I used is of reasonably high resolution but lacks descriptive metadata on crucial points such as acquisition dates and sensors. Closed commercial data is expensive but much better documented.

I thereby already identify two ways in which ethical issues could be alleviated by the application of greater financial resources - resources which are not available to most potential users. This is a major roadblock on the way to unlock one of AIxEOxRS great potentials - to integrate people from diverse backgrounds and domains in creating a better understanding of our world. We have to ask ourselves then, whether the realization of this potential justifies certain errors. If -and under what circumstances- a study based on flawed data is still preferable to no study at all. Whether the nature (remote, open, to some extent detached and objective) of openly available AIxEOxRS data and methods does more good (via allowing the study in the first place, facilitating exchange, diversity and ideally even greater objectivity) than it does harm (via discrimination and errors)?

Taking this perspective, we have to consider the utility of the results of the study and the data it generated, by weighing positive and negative outcomes. This then very much depends on the application the results are used for. And in that, the researcher has a crucial role.
They should discuss which applications are supported by the data. As the URISA code states: "*Be forthcoming about any limitations of data, software, assumptions, models, methods, and analysis.*" More than this, I believe, the researcher must concern themselves which uses of the data may be possible (considering both technical limitations, but also the socioeconomic and political situation), and which of these possible uses are supported by the data.
In my concrete example, the accuracy is sufficient to allow descriptive, aggregated statistics such as estimates of the area covered by UVs. Or, more precisely, the area covered by an urban morphology that UVs often exhibit. This can allow us to find trends of urbanization on a coarse level, such as for cities or metropolitan regions. The accuracy is **not** sufficient to allow delineation of individual UVs to the extent that results should be used for urban planning.
Interpretation of the errors (Type I and Type II Errors) also depend very much on the application. For example, an application might have a high cost for Type I errors (of commission) but a negligible cost for Type II errors (of omission). Which applications can be supported will not be obvious for non-experts. Therefore, I believe it is the responsibility of the researcher to address this in the discussion or metadata of the published results. This directly reinforces transparency and the chances of beneficial use and indirectly allows for greater accountability and stakeholder participation. Myself, I did not do this. While I did spend time contemplating the topic of appropriate use privately, I did not discuss it in the publication. In hindsight, I believe that a short discussion would have been warranted.
An alternative may be to refrain from the publication of the study altogether. I think this should be considered if the error is too high and continued development would likely lead to immoral outcomes. The AIG suggest: "*In situations in which no ethically acceptable trade-offs can be identified, the development, deployment and use of the AI system should not proceed in that form*". Application of a duty or virtue based ethical approach could also suggest that certain methods are never acceptable. Until agreements and regulations are in place, we could consider a moratorium on entire branches of technology, such as facial recognition technology (Crawford, 2019; Weise and Singer, 2020). However, excepting extreme cases, that does not mean that development should stop completely. Rather, one should strive for clarity and transparency about the inaccuracies and errors. This, in turn, can allow for discussion and development of regulations on or improvements of the system. A lack of technical robustness is not an issue that can never be overcome. If the system in question is a) not deployed in decision making b) handled with transparency, openness, and stakeholder involvement then the errors that can be caused by openness (of data) can also be solved by openness (in development and auditing).
Creating transparency can be technically challenging, however, especially if the system uses complex models. Especially deep-learning based models are notoriously large and difficult to

interpret. In my case even I, as the developer of the workflow, spend little time testing the model itself, which I treaded much like a black box. While I understood the theoretical workings of the algorithm, I did not understand the learned criteria by which the trained model finally made its decisions. That is not to say that this would have been impossible. Taking additional steps could have increased transparency: Additional testing and would have allowed me to find patterns in the model's errors and I could have implemented XAI techniques to make the model itself more transparent. The latter, however, required knowledge I do not possess. It is clear that even if the will to create transparency is there, creating it is not trivial and requires investment in resources. I find, however, that the barriers become increasingly lower, with more toolsets being released and the XAI field gaining prominence(Bellamy et al., 2018; Wexler et al., 2019).

It is important to note that errors in my labeling are not the only possible sources of discrimination. If the reality is unfair, correctly labeled data will reflect those biases. In the case of UVs, they are often home to large numbers of migrant workers, which are restricted from formal urban housing. The housing of these groups is disproportionately more likely to be classified as UV. Is this a case of bias? I would say so. Is it unfair bias? And, if we are dealing with unfairness, is it reasonable to expect of me to account for this in my project? To answer this question would require an understanding of the UV discussion that I do not possess. A lot depends on the social status and history of the groups that are disproportionately affected, and if this is the topic of a political debate. Even on a pure a statistical level, to recognize and correct for bias, the protected labels (in this case, some form of geographical origin) need to be known. No such data was available to me.

My literature review indicates that there is indeed controversy and political debate regarding the status of UVs, especially with regard to their redevelopment into formal urban spaces. It is possible that much of this is not available in English and was thus not considered by me. I still believe it is my responsibility, within reason, to firstly consider possible outcomes (as proposed by the URISA code) and secondly discuss them with stakeholders (as suggested by the URISA and AIG). I have failed to do the latter. It is likely that my research, seeking purely to prove the validity of a method, will have negligible political effect. From a consequentialist point of view, that may liberate me from the threat of ethical errors. If we consider possible duties and virtues of scientists, we must concern ourselves with the question whether science ought to be political. That is a topic beyond the scope of this essay.

Modeling the Spatial Distribution of the Common Jogging Human

Project Summary

As an exercise in Species Distribution Modelling, I was interested to research where joggers can be found in my University Town of Würzburg - what environmental and social factors predict

their presence (Mast, 2019). To do this, I combined jogging tracks and several predictor variables in an ensemble of different models.
Acquiring the jogger's tracks - the presence data of the "species" - was the first step. Many athletes use GPS devices to track their progress. The sharing of such data has led to controversies, as in the case of the company Strava. In one case, Strava published a heatmap of the user's running tracks which led to the identification of military bases (Schwartz, 2018) . Further controversy came from Strava's policy to automatically share tracks with other users (Ballinger, 2020). While such data would have been great for my research purposes, it was only commercially available at the time. It has since been made easier for developers to access Strava data, with the release of the Strava API and Strava metro becoming free for city governments to use (Reid, 2020). In my project I resorted to voluntarily uploaded jogging tracks from Runnersworld.com. An API was not available, so I manually downloaded all available 111 running tracks for Würzburg. I removed any metadata except the geolocation from the tracks.
I acquired openly available SRTM and Sentinel 2 data which served to create environmental parameters. Further, I included several other variables which I suspected may be suitable predictors for the attractiveness of an area for joggers:
I downloaded OpenStreetMap (OSM) Data containing the locations of paths and streets, which were used as input variables.

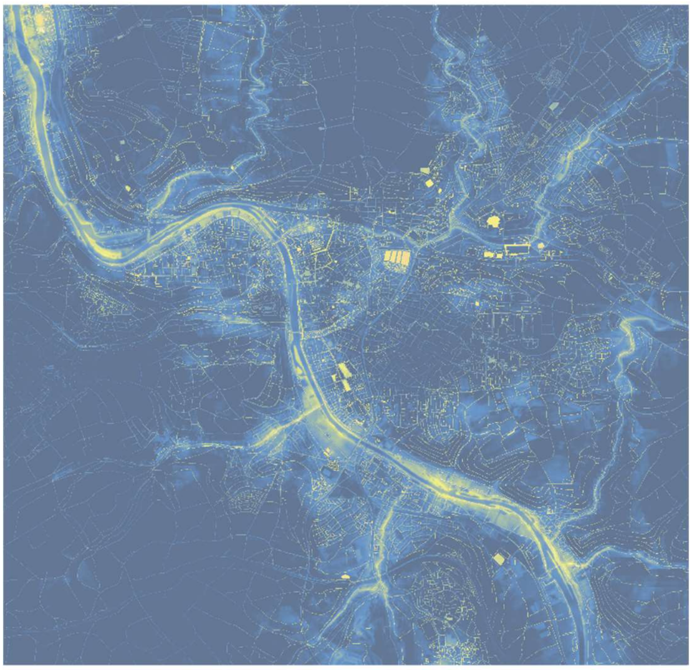
Figure 6: Results of the ensemble model trained on the presence of joggers in Würzburg.

I further used OSM data also as a source for industrial and residential buildings and water areas. I calculated the proximity to such locations and used them as input variables to the model.
I finally downloaded Flickr images of private users via the Flickr API (Flickr, 2018). I stripped them of any metadata except their geolocation. The images were then classified as "*Manmade*" or "*Natural*" using a model pre-trained on the places dataset (Zhou et al., 2018). I used the classifications to create additional variables which were intended to serve as a proxy for the naturalness. It has later come to my attention that the download of Flickr images through the API is not always allowed (Flickr, 2020) even when the API supports this and the images are public. In my download I did not

consider this, although I suspect it would have been easy to check. Whether it would have impacted the quality of the result I do not know.
To create a robust result, several simple models were used in an ensemble. The result was a map of the predicted species distribution.

Discussion of the Project

My sample was clearly biased. The running tracks only included tracks from people who voluntarily uploaded data on a platform - therefore, I assume that the sample is biased towards people with a certain tech savviness and interest in running. This is a general issue with VGI. In this case, I did not mention the biases of my sample on the poster I created on the study. Although a poster only presents a limited space, in hindsight I believe that it was wrong to exclude this information, as it is crucial for the interpretation of the result. Because I was not forthright about the limitations of my data, transparency, and, to an extent, accountability suffered to a degree.
Care must be taken with the interpretation of the result, as it does not represent the real distribution of joggers or the attractiveness areas for joggers, but rather extent to which an area matches (within the predictor variables used) those areas where joggers are found. Imagine, for instance, a park on a peninsula in the river that can only be reached via a street which leads for many kilometers through an industrial area. Such a park would in practice be neither an attractive destination nor would it receive any visitors. My models, however, would give this park a very high value. They also gave a very high value to public cemeteries. This, I believe, is a good example of the dangers of maps, especially when created by AI. They are intuitively understood and often look plausible, inviting a large degree of trust, even when they fail. Often, their failure is not so much on the AI itself, but rather a misalignment between the goals of the AI and the goals of its human operators and interpreters. Even my comparatively simple model had outputs which were mathematically correct, but can be easily misunderstood, and it had fundamental limitations which are not obvious. Transparency is all the more important. Reflecting upon this project, I decided to, going forward, make it a priority to communicate the limitations of my methods.
That is not to say that more complex models would not be able to overcome those limitations and do a better job by taking into account non-Euclidean distance metrics and additional variables in complex nonlinear relationships. While this would likely require a much larger training dataset - companies like Strava certainly possess such. Mapping the attractiveness of areas is possible. Unless additional measures for debiasing are taken, such maps will inherit the biases of the data and of the people who supply the data. This is concerning when we consider that such maps could figure into calculations of land prices, having a real impact on property values, and people's lives. As Nemorin and Gandy (2017) point out, disadvantaged groups often suffer the most from algorithmic scoring. Instead of improving society through greater knowledge, the technology then reinforces existing injustices. To recognize and remedy

violations of fairness, greater accountability, robustness, and transparency are absolutely required, and the impact of such mapping projects must be carefully considered.
Finally, the use of Flickr imagery comes with some uncertainties regarding the fair use of uploaded images. Users uploading their imagery did consent to the public availability of their images. However, they did not consent to this specific use of their data, and as such, it could be argued that their consent was not truly informed. How can and should application-specific consent be acquired? I have no answer to this question. Lacking that, I am sure that one should err on the side of caution when handling such data. I believe the measures I took are sufficient for this project and this point in time. But with ever increasing power of AI, privacy measures need to be continuously reevaluated and improved.

VHR Segmentation of Agricultural Fields

Project Summary

In this study project that was inspired by a greater research project (LandKlif, 2019), I developed methods for the purpose of delineating agricultural fields at a number of sites in Bavaria. Initially I employed simple, handcrafted models with low technical requirements and good interpretability (Blaschke, 2010). These, however, proved to have little robustness towards changing conditions, especially changes in illumination. Resorting to machine learning, I adapted the Mask R-CNN (He et al., 2018), which was at the time the state of the art in instance segmentation.
As I did not have practical access to powerful hardware, I developed and tested the network in the cloud platform Google Colab. This, however, resulted in difficulties with the data that was used in the project. This data was provided by the Bavarian Landesamt für Digitalisierung, Breitband und Vermessung (LDBV). Because sharing data with a third partner such as Google was not permitted within the project, I was unable to use the research project-internal imagery. I resorted to using Microsoft Bing Maps imagery which was publicly accessible under the Bing Maps educational license (Microsoft, 2020a), to the limit of 50,000 cumulative billable transactions within any 24-hour period. This Bing imagery, however, proved to be lower in

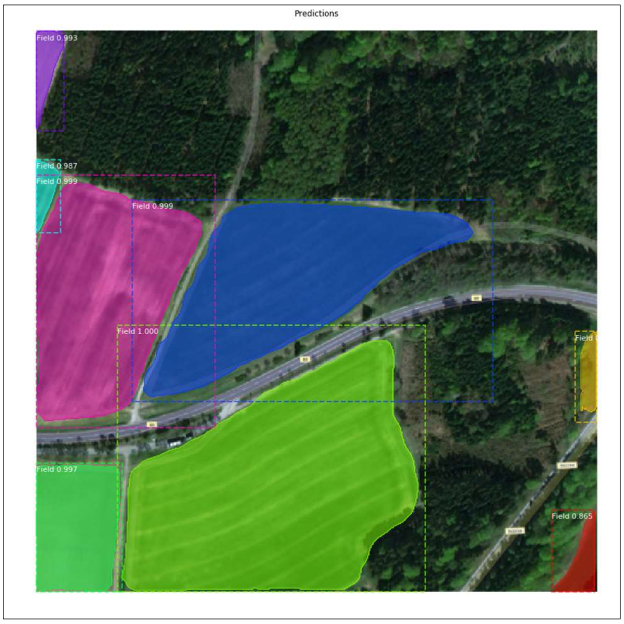

Figure 7: Predictions of the Mask R-CNN. In color the extent of the detected agricultural fields. Basemap: Bing Maps

consistency and quality than the project-internal data. Further, little metadata was available for image tiles, making it difficult to assess when an image was taken.
I trained the model using labeled data which I manually collected using visual inspection of the Bing imagery. The trained model produced results whose quality and robustness far exceeded any of my previous attempts. I was never able to apply it on the project internal data. Unfortunately, due to the limitations of the educational license, I was also not able to share the project's code freely. Anyone using my code needs to provide either their own resources and data or their own Bing Maps license.
Discussion of the Project
The project-internal data was not open. This closedness of the data is propagated through the study from the input data to its outputs. As a result, I was not able to freely share the results of the study-project. Such sharing would have been desirable for me personally, as an opportunity to show my skill, and to invite feedback for further improvements. Accountability would have been improved as anyone would be able to replicate my results. The alternative data source, Bing Maps, was free to a certain degree and more open, but less consistent and less documented. This, too, was propagated to the study outputs, greatly reducing their practical utility. For instance, while the model is highly accurate in delineating fields on images, that delineation is of limited use when the acquisition time of the image is not known. This is more problematic the more dynamic the observed surface is.
There is, of course, the option to go back to the originally hand-crafted models. This would have meant trading off robustness and performance for greater openness and interpretability.
To an extent, the issues of openness could have been solved in different way by application of greater resources: Either to acquire higher quality imagery, to procure access to the necessary hardware, or to a more extensive license. They could also have been solved were the project internal data open. Large amounts of RS data are already openly and freely available: The Landsat, MODIS and Copernicus programs provide state-of-the-art satellite data. The availability of the more highly resolved aerial imagery is inconsistent. The German state of Thüringen offers it openly and freely for download (without registration), for the state of as Bavaria, within which my project was conducted, this is not the case. As of the writing of this document, the cost of a km² of Bavarian aerial imagery is 6€ (Bayerische Vermessungsverwaltung, 2020a). For my project, this would have meant a total cost of thousands of euros. Even then the sharing of the data and results may not have been permitted by the terms (Bayerische Vermessungsverwaltung, 2020b) unless such permission was granted by the LDBV. The resolution of such aerial imagery is 20cm, easily enough to identify individual objects on private property. On a personal level, I would have loved access to this data, and the opportunities it provides. But should it be open to everyone?
It could be argued that it is unethical of the LDBV to restrict access to data for which taxpayers have already paid. That the restriction is protecting privacy of individuals may be a valid

argument if the restriction did not come in the form of a financial cost. As it is, it merely prevents privacy intrusions from people without the necessary funds. If there are concerns about privacy, they should be addressed by a more equitable and fair restriction. I believe that it would be difficult to agree on such a restriction due to the large variety and constant improvement of RS datasets. The public's awareness of such datasets is also an issue, particularly when we try to draw the line at some variation of expectation of privacy (Cornell.edu, 2020). Legal restrictions could be tied to the data's resolution. High resolution imagery, like the ones increasingly gathered by unmanned aerial vehicles, could be artificially downsampled. This, however, might also be limited in protective power as it is not only the resolution that keeps increasing – our ability to extract information from images is also continually enhanced by AI (e.g. Superresolution (Fernandez-Beltran et al., 2017)). Keeping legal restrictions up-to date is challenging. Ethics can and should be more flexible and up-to-date than the often lagging legislature of countries (compare Thiroux, 1986; cited in Wasowski, 1991). While Ethics should not serve as a replacement for regulations, or even a way to escape from them (Wagner, 2018) they can serve to fill the gaps until regulations are in place. When it comes to the conflict between privacy and openness, the AIxEOxRS community could build on their own ethical codes and try and find compromises. They could also look towards other fields. Within the domains of management, psychology, and social work, to my knowledge, a number of frameworks for resolving dilemmas exist (Craft, 2013; Dolgoff et al., 2012; Dubinsky and Loken, 1989; Strom-Gottfried, 2014). These could guide the development of strategies specific to AIxEOxRS. The community could also agree on a specific framework of normative Ethics and try to resolve the conflicts on that basis.

Taking a utilitarian perspective, it is plausible that the goal should be to maximize the utility of public good that results from the shared cost of AIxEOxRS projects. If the expected utility is large, the decrease in privacy may be justified under such an approach (compare Harris, 2013). Is that the case here?

The application of AI for agricultural monitoring is a sector experiencing a large commercial growth, and the benefits range from reduction of environmental issues, lower resource consumption due to precision farming. It is likely that the public benefits from this sector in more ways than one. If data and methodology were openly shared, it may facilitate the development and quality of algorithms. Still, the reverse may also be possible: That openness de-incentivizes development due to freeloader effects. If there were a law mandating openness, it may largely remove economic incentives from the developers. A reduction of R&D spending in this sector might then reduce the overall benefit that is gained from the RS data despite its greater availability. If we keep following a utilitarian perspective, the costs and benefits become difficult to evaluate. I refer to (Bostrom, 2017) for a general discussion of openness in AI, much of which is applicable to the topic of this essay.

I believe that issues of openness can be approached with a utilitarian and economic perspective. However, evaluating the costs and benefits of publishing datasets can be very complex. Depending on the type and resolution of the dataset, these can vary strongly. Deontological Ethics face a different problem: They would require a shared concept and acceptance of privacy which is not found. As many AIxEOxRS methods and data are global, they affect people of many different cultures, with different expectations of privacy. As Carr et al. (2014) put it, Ethics in geospatial data is a moving target due to societies changing expectations. I think it is unlikely that the specifics of the rights and obligations can be figured out, especially since the power of AIxEOxRS and its acceptance by the public are likely to keep changing.

Discussion

Questions of **openness of data** arose in all examined projects. I identify two groups of issues: The first concerns the quality of open data, which is usually worse, and the second concerns the desirability of openness of data in general.

On the first issue: AIxEOxRS can and does make use of both free and open as well as closed and commercial data. Often, the commercial data is of higher quality. As a result, works relying on open data tend to perform worse in fulfilling technical and even ethical requirements. If such works should still be judged positively is a matter of outcomes and priorities. With freely available data, AIxEOxRS has the potential to allow anyone to participate in the mapping of the earth. It allows for diversity, stakeholder inclusion, and a plurality of worldviews. Those are weighed against the lower performance of open data in matters of accuracy, robustness, and bias.

If the political will to do so exists, one possible solution is to simply make larger amounts of high-quality data open, via policies or greater allocation of financial resources. The data of the COPERNICUS program is already completely open, and as we have seen in the example of Thüringen, states and countries also increasingly open their archives.

That leads to the second group of issues: Inherent downsides of opening data. Openness is intrinsically at odds with privacy. Both cannot be fully realized at the same time. Open data may reveal private details of individuals or it reveals the location of protected sites. Such reveal should be expected to be irreversible: the internet, at least, does can not be expected to forget. Freely giving away data may also disincentivize development. Closing data behind a paywall is likely not the optimal solution from an ethical perspective, as commercial interest does not necessarily align with the interest of the public. As a consequence, data acquisition and analysis of environmentally sensitive areas may be reduced in favor of monitoring more immediately profitable sites - a concern already brought forward by Wasowski (1991) Finally, if research produces output data which can be harmful, openness as a non-negotiable imperative might not be the way to go.

Perhaps less controversial is another recurring issue: That of **transparency of methods**. This connects to my previous observation that the field of AIxEOxRS receives a great deal of trust that it could lose. To avoid this, capabilities, limitations, and errors must be communicated clearly. I believe transparency is easier to realize than openness, for two reasons: *Firstly*, unlike openness, transparency is not strongly at odds with other ethical requirements. To the contrary, it can facilitate them.

Secondly, there exist increasing numbers of toolkits and guides for XAI, ML fairness, and platforms to publish models to the community. These technical solutions, as well as many non-technical solutions, can be adopted trans-domain. This will still require effort on part of the developer, delaying developments. However, I am sure that increases in transparency come with benefits towards performance, robustness, fairness, and eventually, trust. As such, I believe that employers and the community at large will recognize that pursuing increased transparency is a worthwhile investment of effort and resources. It will prevent the over-selling of the capabilities and ensure the field's long-term health. Full transparency may not be desirable for methods that can potentially be harmful. Therefore, the release of methods and trained algorithms must be accompanied by critical evaluation of its potential impacts and misuse.

In none of my projects have I spent a significant amount of time considering the societal and environmental **impacts** of my work. They were study projects, merely intended to practice my skills. Documentation and publications that were produced as outputs were more of a side-product, although their production was highly instructive es well. Compared to the time I spent on the data collection, I spent a negligible time pondering potential impacts. That may be justified considering the small scale of the studies. However, I should have taken the opportunity to practice impact assessment to a larger degree. For orientation, I could have looked towards frameworks for impact assessments which already exist and are being further adapted (Ortolano and Shepherd, 1995) (Reisman et al., 2018).

Unfairness is a problem that was underexplored in my UV study, and it could have appeared in the Jogging study as well. Despite the increased availability of toolkits (Bellamy et al., 2018) (Microsoft, 2020b)creating fairness in the statistical sense is not simple. Many notions of fairness exist and cannot all be fully realized. Further, to recognize unfairness, whether in the inputs to a system or its outputs, one needs to have information on the protected labels, which can be gender, ethnicity, or others. Such data could come from existing databases, ground surveys, or expert knowledge. When using RS data, such data is often limited or completely unavailable, as that is a prime motivation for using RS in the first place. AIxEOxRS may thus be particularly vulnerable to commit errors of unfairness. In general, applying anti-bias preprocessing increases fairness, but reduces the measured accuracy of the algorithm. Adversarial debiasing increases complexity. There are, therefore, ethical tradeoffs to be made between different requirements, even within one ethical code, such as the AIG.

Proxies were used in some form in all my projects. It is common to RS, where vegetation health or population density cannot be measured directly, to instead use proxies like reflectances and built density respectively. This necessitates that the relationships between the unobservable and its proxy are understood. In some cases, those relationships are well researched, and based on physical models, such as the calculation of vegetation density in the GEDI project. In others, the relationship is based on machine learning, and not easily explained, as in the case of classification of locations into "*natural*" and "*manmade*" categories based on Flickr images. The use of proxies which are not well understood is, I believe, an area of particular concern for AIxEOxRS, due to the combination of remoteness and opacity.
Curiosity and the goal of self-improvement have been my primary drivers in all these projects, and I am sure those are worthy motivations from an ethical standpoint, as the URISA and ASPRS codes signify. Yet, if practice is the goal, then I should also have practiced this: To consider actions and outcomes from an ethical perspective. And further to discuss them with at least peers, but ideally also stakeholders and teachers. I believe I am not alone among my peers in having neglected this (Harris, 2013). This essay is one way I attempt to remedy that neglect on my part.

4. Literature Review

I further searched using Google Scholar and Semantic Scholar for the keywords "*Ethics*", "*Earth Observation*", "*Remote Sensing*", and "*Geography*". I found surprisingly very little. Only around a dozen articles concern themselves with the Ethics of what I consider AIxEOxRS. Approximately two dozen more touch on aspects of the domain's Ethics in a wider sense. My goal here is not to provide a structured review of all existing works, but rather to identify frequent or interesting topics.
Advocacy and the political use of AIxEOxRS
The question whether EO should be used for political purposes is addressed by Eyres (2017) who presents the opposing views of Tamsin Edwards and James Hanson on the matter. Interesting is the view of former ESA Director Johann-Dietrich Wörner, that the COPERNICUS program should be non-neutral as well as being non-political. Interestingly, Eyres advertises EO's untapped *artistic* potential. I agree that such potential exists and brings particular power to influence opinion. This is a unique characteristic of AIxEOxRS that requires consideration.
Teaching and furthering Ethics in AIxEOxRS
A number of articles concern themselves with the (lack of) ethical discussion in the field and how it can be furthered. Slonecker (1998) states that concerns about RS have always existed, but it has never caused problems due to technical limitations. In the field that I come from, physical geography Proctor (1998), identifies a lack of attention towards Ethics that he suspects is

historical rather than inevitable. In Human Geography, Ethics is discussed more frequently (Olson, 2017) and textbooks on the subject exist, such as Wilson and Darling (2020).
A journal about Ethics and Geography has also existed for a while under the name "*Ethics, Place & Environment*" (Proctor, 1998). This has since been renamed to "*Ethics, Policy & Environment*".
That Ethics receives greater focus in the human branch of geography is understandable. I believe that knowledge can partially be adopted into the AIxEOxRS field, when topics of human geography are addressed.
Teaching Ethics in RS courses has been suggested 20 years ago and by multiple authors. A study by Wetherholt et. al in 2007 found that 52 percent of respondents teaching remote sensing at US colleges and universities already include ethical use discussions (Wetherholt and Rundquist, 2010). One respondent in the survey responded to decidedly not include ethical discussions because, according to the respondent, the majority of RS applications are uncontroversial, and that time should rather be dedicated towards teaching about the many useful applications. That the investment of time and effort to create Ethics-focused courses can pay off is shown by the example of van den Bemt et al (2018). Yet it does always put additional requirements on teachers and students. I find that the interdisciplinarity of AIxEOxRS already requires students to learn about a large variety of different subjects. Introducing Ethics as another subject indeed takes time from the thorough study of the tools of the trade and the proper background of possible applications. This reduces the chances that fitting applications are identified, that the right tools are chosen for the application at hand and increases the possibility of factual errors. In this way, neglecting the core skills of the AIxEOxRS can have unethical consequences in their own right. I believe this is especially the case for statistics and machine learning. From my experience, many of us use statistical methods daily, and in practically any task. Despite that, few of us are formally trained in statistics and many of our skills are acquired practically. A concern for me is the risk that I understand the methods well enough to use them, but not enough to spot their failures. Fortunately, openness and the consultation of experts can alleviate this issue.
I believe Ethics can and should be integrated into the curriculum to an extent. In my study program, ethical issues are rarely raised explicitly, but are occasionally discussed on a per-application basis. That makes Ethics more approachable and fun. Further, it avoids the risk that the mere prescription of mandatory Ethics can lead to a mentality of box-ticking (van den Bemt et al., 2018).
At the very least, students should be made aware of resources like the ethical codes and encouraged to resolve dilemmas through discussion and consultation of peers, experts, and stakeholders. As Proctor (1998) notes: Getting started is the most important thing. Students, for who getting started is part of their job, should be receptive to this philosophy. Reaching practicing data and computing professionals may be much more difficult. Carr et al., (2014) finds that they tend to regard ethical concerns as either irrelevant to their research and

development activities, or a barrier to getting their work done. I can imagine that in a business environment expenses of time and budget need to be justified. Garzcarek and Steuer (2019) suspect that among data-scientists there may be a lack of engagement with ethical matters that is grounded in some idea that it is professional to appear de-personalized.

Potentials of Openness

Openness is often discussed with regards to the potential for involvement of people through citizen science.

The potential of openly available data for citizen science is recognized by Eyres (2017). Multiple goals can be reached by this: *Firstly*, common people can hold corporations and states accountable (Eyres, 2017; Harris, 2013; Myers, 2010). *Secondly*, previously unconnected stakeholders can be connected (Eyres, 2017). Thus, greater diversity may be achieved, and we may go beyond researching what Lawhon et al. (2014) call what "*White people want to know*". Incorporating diverse interests does not come without challenges. Situations may arise in which different epistemologies result in competing worldviews and accounts. Situations may arise in which our RS derived knowledge even differs from the gathered ground-truth provided by participants and stakeholders (Lawhon et al., 2014). Our truth-seeking process will be complicated. However, that should not discourage us from involving people with different opinions and backgrounds. Cochrane et al. (2017) who cites Harley (1990) notes, "*Cartography, we see, is never merely the drawing of maps: it is the making of worlds.*" I think that the making of worlds should not be restricted to a particular group of people. And whether or not there is an objective truth about the environment to be found, it is worthwhile to consider different views held by different people. Because those views determine how people shape their environment. Openness allows for citizen science which in turn furthers accountability, diversity, human agency, stakeholder participation and science as a whole. However, it provides challenges in terms of realising data access and communication. These challenges, mostly technical, are being overcome more and more. However, as I have discussed in my project review, there are more controversial aspects to openness. Openness is fundamentally at odds with privacy and national sovereignty (Wasowski, 1991). We must also consider that AIxEOxRS data and methods intended for good purposes can be misused (Slonecker, 1998). For example, Google Earth has been used in the planning for both humanitarian purposes as well as terrorist attacks (Harris, 2013; Wetherholt and Rundquist, 2010). The combination of several forms of information, each in itself rather benign, could develop capabilities that many people would consider to be objectionable or even dangerous (Wetherholt and Rundquist, 2010). The position of AIxEOxRS at the intersection comes with responsibility to evaluate the benevolence of joint use of data and methods, and whether opening them is justified.

Wasowski (1991) worried that developing nations might be forced out of the market due to limited accessibility of the data, software, and processing capabilities. Thirty years later, I find that this gloomy scenario has been averted. Many AIxEOxRS resources are openly available.

While the development of the state-of-the-art AI systems is only accessible to the richest countries and organizations, powerful models are often shared. Whether the gap is closing or widening is difficult to tell. It is likely and understandable that organizations at the forefront of development are keeping the best models to themselves. Whether this is also beneficial is a complex question beyond the scope of this essay.

Openness serves multiple benefits and is from a utilitarian standpoint often justified. It may also be motivated deontologically. As Harris (2013) puts it: Google Earth's open data policy is "Duty Ethics in Action". I believe that a more restrictive approach also has its merits and should not be dismissed outright. But we must take care that restrictions to access do not reinforce existing power disparities.

Privacy

Closely connected to matters of openness is privacy. While in the past, privacy concerns were limited due to the limited power of RS (Wetherholt and Rundquist, 2010) that is increasingly changing. Myers (2010) goes as far as calling Google Earth a global panopticon, more insidious even than the original design, that is now widely available. Soroka and Kurkova (2019) recommend a proactive approach, in which the use of AI is monitored by both laws and active participation by stakeholders and human-rights experts. I also believe that in addition to fixed regulations, active participation is needed. Both technology and society's expectations are changing quickly, and are a moving target for Ethics and law (Carr et al., 2014). To what extent regulations such as the GDPR (EU, 2016) will stand the test of time, I cannot say. If they do not, updates can be incremental and need not be large, but should be discussed. There are many possible causes of ethical errors, but negligence and complacency should not be one of them.

Social Justice and Moral Geography

Cochrane et al. (2017) find that there is very little writing on social justice in the field. I find it worth noting that it would be wrong to assume that Ethics and morals are a one-way street. While AIxEOxRS can and should learn about Ethics from fields like human geography, the reverse is also possible. AIxEOxRS can contribute valuable insights to the way humanity shapes its environment, and contribute to the fields of Social and Moral Geography (see Olson 2017 for relevant considerations) and thereby further our understanding of morality, Ethics, and justice.

5. Conclusion

The codes are very general and unspecific. On their own, they provide little practical help, particularly with resolving dilemmas, but they can serve as a basis for ethical discourse and a source of inspiration for solutions. The AIG further provides concrete suggestions for AI assessment. Despite differing theoretical foundations, the codes agree on many matters, and I believe that it is in practice possible to use them in conjunction. Domain-specific adaptation is absolutely required. On their own, the codes have very little practical worth, and if they are used for nothing more than creating the appearance of ethical standards, they may even do more harm than good. If, however, work gets put in to make them more concrete, to develop real domain-specific prohibitions and descriptions, ethical targets, and technical ways to reach them, then the codes can become the core of something significant.

Challenges to the creation of a domain-specific code are the multidisciplinarity of the field and its quick technical development. I believe the question of who should be involved in the creation of a code will be crucial. Public debate on ethical issues will be beneficial regardless of the course taken, but it will involve uncomfortable conversations and compromises. To address conflicting ethical requirements, I believe the field could benefit from adapting concepts of ethical decision making from other domains. Other ethical requirements can be furthered by the allocation of greater resources and the adaptation of technical solutions from other fields. The AIxEOxRS community should strive to be receptive to such opportunities and give them platforms for discussion.

There is no blind spot at the intersection of the AI, EO, and RS codes. Someone following all three codes would have to consider the unique issues of AIxEOxRS as well. However, that does not diminish the need for a true AIxEOxRS code, but rather emphasizes it.

In the review of my practical work, issues of openness, privacy and data quality are the most salient. I find that while for many topics, open data and resources are available, they often come with certain caveats that limit use and performance. Despite the limited scope of my studies, I should have considered the consequences of my work more and I will make an effort to be more aware in the future. I also find that transparency is desirable, particularly about limitations of the method and quality of the data. Here, as well, I will try and do better in the future.

Across codes, my own projects, and literature, I also find that issues of openness are prominent. Openness of data and method is widely practiced in the field and provides many benefits to accountability, citizen involvement and scientific progress. But it is not necessarily universally desirable, as openness of private or dangerous information and technology might endanger individual privacy, state-sovereignty, and public well-being. Dilemmas such as this should be resolved by consideration of the ethical codes, and via discussion and engagement of different stakeholders.

To ensure that parties are capable of discussion, Ethics must not be neglected completely in the RS curriculum. The importance of explicitly teaching Ethics should not be overstated, however. In my opinion, the study and practice of solid methodological foundations and application-specific knowledge can go further in avoiding critical errors, even ethical ones. In a similar vein, because some ethical issues can be resolved via technical solutions and greater resources, students, researchers, and professionals should make a personal effort to remain aware of developments in related fields such as XAI.

Finally, AIxEOxRS has the potential to do a lot of good. Promoting its use for benevolent applications is a worthwhile goal in itself. And ensuring that this use is ethical will not hinder the flourishing of the field, but rather, safeguard it. Ethics should not be seen as a roadblock towards the field's development, but a strategy to ensure its health and cement its place in science and society.

About the Author

I am a student enrolled in the EAGLE master program at the chair for remote sensing at the university of Würzburg. The chair is held by Prof. Stefan Dech, also head of the German Remote Sensing Data Center (DFD), with which the program is tightly associated. The EAGLE program provides methodological knowledge as well as practical skills as well as an overview of applications. I hold a B.Sc. in Physical Geography with a specialization in Geoinformatics and have become familiar with the basics of Remote Sensing and Artificial Intelligence but am neither trained in Data Science nor Ethics. My primary research focus is the Geography of the urban environment.

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Appendix A: ASPRS Code of Ethics

Honesty, justice, and courtesy form a moral philosophy which, associated with mutual interest among people, should be the principles on which ethics are founded.

Each person who is engaged in the use, development, and improvement of the mapping sciences (Photogrammetry, Remote Sensing, Geographic Information Systems, and related disciplines) should accept those principles as a set of dynamic guides for conduct and a way of life rather than merely for passive observance. It is an inherent obligation to apply oneself to one's profession with all diligence and in so doing to be guided by this Code of Ethics.

Accordingly, each person in the mapping sciences profession shall have full regard for achieving excellence in the practice of the profession and the essentiality of maintaining the highest standards of ethical conduct in responsibilities and work for an employer, all clients, colleagues and associates, and society at large, and shall

1. Be guided in all professional activities by the highest standards and be a faithful trustee or agent in all matters for each client or employer.
2. At all times function in such a manner as will bring credit and dignity to the mapping sciences profession.
3. Not compete unfairly with anyone who is engaged in the mapping sciences profession by:
    a. Advertising in a self-laudatory manner;
    b. Monetarily exploiting one's own or another's employment position;
    c. Publicly criticizing other persons working in or having an interest in the mapping sciences;
    d. Exercising undue influence or pressure, or soliciting favors through offering monetary inducements.
4. Work to strengthen the profession of mapping sciences by:
    a. Personal effort directed toward improving personal skills and knowledge;
    b. Interchange of information and experience with other persons interested in and using a mapping science, with other professions, and with students and the public;
    c. Seeking to provide opportunities for professional development and advancement of persons working under his or her supervision;
    d. Promoting the principle of appropriate compensation for work done by person in their employ
5. Undertake only such assignments in the use of mapping sciences for which one is qualifed by education, training, and experience, and employ or advise the employment of experts and specialists when and whenever clients' or employers' interests will be best served thereby.
6. Give appropriate credit to other persons and/or firms for their professional contributions.
7. Recognize the proprietary, privacy, legal, and ethical interests and rights of others. This not only refers to the adoption of these principles in the general conduct of business and professional activities, but also as they relate specifically to the appropriate and honest application of photogrammetry, remote sensing, geographic information systems, and related spatial technologies. Subscribers to this code shall not condone, promote, advocate, or tolerate any

organization's or individual's use of these technologies in a manner that knowingly contributes to:

a. deception through data alteration;
b. circumvention of the law;
c. transgression of reasonable and legitimate
d. expectation of privacy.

Appendix B: URISA Code of Ethics

On April 9, 2003, the URISA Board of Directors unanimously approved the "GIS Code of Ethics" proposed by the URISA Ethics Task Force.

The Code of Ethics is intended to provide guidelines for GIS professionals. It should help professionals make appropriate and ethical choices. It should provide a basis for evaluating their work from an ethical point of view. By heeding this code, GIS professionals will help to preserve and enhance public trust in the discipline.

The text of this code draws on the work of many professional societies. A few of the guidelines that are unique to the GIS profession include the encouragement to make data and findings widely available, to document data and products, to be actively involved in data retention and security, to show respect for copyright and other intellectual property rights, and to display concern for the sensitive data about individuals discovered through geospatial or database manipulations.

The Code of Ethics document is the result of extensive public review. Dozens of people provided useful feedback and suggestions during two periods of open public comment in 2002. All comments were reviewed and considered carefully.

The Code consists of these four primary categories:

I. Obligations to Society
II. Obligations to Employers and Funders
III. Obligations to Colleagues and the Profession
IV. Obligations to Individuals in Society

Will Craig, University of Minnesota, and Chair of the Task Force feels it is important for a profession to have a Code of Ethics. "It's not that we expect the Code will be a front-line of defense against wrong-doing. Instead, the Code provides a touchstone for members to identify and resolve ethical dilemmas that they encounter in their work."

The Code of Ethics Task Force was a subcommittee of URISA's Certification Committee which developed the GISCI Certification Program. Individuals seeking certification must also certify that he or she has read and agrees to conduct professional activities in conformance with the professional Code of Ethics. Thus, conducting professional activities in an ethical manner is part and parcel of the GIS Certification Program.

GIS Code of Ethics

This Code of Ethics[1] is intended to provide guidelines for GIS (geographic information system) professionals. It should help professionals make appropriate and ethical choices. It should provide a basis for evaluating their work from an ethical point of view. By heeding this code, GIS professionals will help to preserve and enhance public trust in the discipline.

This code is based on the ethical principle of always treating others with respect and never merely as means to an end: i.e., deontology. It requires us to consider the impact of our actions on other persons and to modify our actions to reflect the respect and concern we have for them. It emphasizes our obligations to other persons, to our colleagues and the profession, to our employers, and to society as a whole. Those obligations provide the organizing structure for these guidelines.

The text of this code draws on the work of many professional societies. It is not surprising that many codes of ethics have a similar structure and provide similar guidelines to their professionals, because they are based upon a similar concept of morality. A few of the guidelines that are unique to the GIS profession include the encouragement to make data and findings widely available, to document data and products, to be actively involved in data retention and security, to show respect for copyright and other intellectual property rights, and to display concern for the sensitive data about individuals discovered through geospatial or database manipulations. Longer statements expand on or provide examples for the GIS profession.

A positive tone is taken throughout the text of this code. GIS professionals commit themselves to ethical behavior rather than merely seeking to avoid specific acts. The problems with listing acts to be avoided are: 1) there are usually reasonable exceptions to any avoidance rule and 2) there is implicit approval of any act not on the list. Instead, this code provides a list of many positive actions. These explicit actions illustrate respect for others and help strengthen both an understanding of this ethos and a commitment to it.

This code is not expected to provide guidelines for all situations. Ambiguities will occur and personal judgment will be required. Sometimes a GIS professional becomes stuck in a dilemma where two right actions are in conflict with each other, or any course of action violates some aspect of this code. Help might come from talking with colleagues or reading relevant works such as those listed in the bibliography. Ultimately, a professional must reflect carefully on such situations before making the tough decision. Contemplating the values and goals of alternative ethical paradigms may be useful in reaching a decision.

- View persons who exemplify morality as your own guide (Virtue Ethics)
- Attempt to maximize the happiness of everyone affected (Utilitarianism)
- Only follow maxims of conduct that everyone else could adopt (Kantianism)
- Always treat other persons as ends, never merely as means (Deontology)

I. Obligations to Society

The GIS professional recognizes the impact of his or her work on society as a whole, on subgroups of society including geographic or demographic minorities, on future generations, and inclusive of social, economic, environmental, or technical fields of endeavor. Obligations to society shall be paramount when there is conflict with other obligations. Therefore, the GIS professional will:

1. Do the Best Work Possible

- Be objective, use due care, and make full use of education and skills.
- Practice integrity and not be unduly swayed by the demands of others.
- Provide full, clear, and accurate information.
- Be aware of consequences, good and bad.
- Strive to do what is right, not just what is legal.

2. Contribute to the Community to the Extent Possible, Feasible, and Advisable

- Make data and findings widely available.

- Strive for broad citizen involvement in problem definition, data identification, analysis, and decision-making.
- Donate services to the community.

3. **Speak Out About Issues**
   - Call attention to emerging public issues and identify appropriate responses based on personal expertise.
   - Call attention to the unprofessional work of others. First take concerns to those persons; if satisfaction is not gained and the problems warrant, then additional people and organizations should be notified.
   - Admit when a mistake has been made and make corrections where possible.

II. Obligations to Employers and Funders

The GIS professional recognizes that he or she has been hired to deliver needed products and services. The employer (or funder) expects quality work and professional conduct. Therefore, the GIS professional will:

1. **Deliver Quality Work**
   - Be qualified for the tasks accepted.
   - Keep current in the field through readings and professional development.
   - Identify risks and the potential means to reduce them.
   - Define alternative strategies to reach employer/funder goals, if possible, and the implications of each.
   - Document work so that others can use it. This includes metadata and program documentation.
2. **Have a Professional Relationship**
   - Hold information confidential unless authorized to release it.
   - Avoid all conflicts of interest with clients and employers if possible, but when they are unavoidable, disclose that conflict.
   - Avoid soliciting, accepting, or offering any gratuity or inappropriate benefit connected to a potential or existing business or working relationship.
   - Accept work reviews as a means to improve performance.
   - Honor contracts and assigned responsibilities.
   - Accept decisions of employers and clients, unless they are illegal or unethical.
   - Help develop security, backup, retention, recovery, and disposal rules.
   - Acknowledge and accept rules about the personal use of employer resources. This includes computers, data, telecommunication equipment, and other resources.
   - Strive to resolve differences.
3. **Be Honest in Representations**
   - State professional qualifications truthfully.
   - Make honest proposals that allow the work to be completed for the resources requested.
   - Deliver an hour's work for an hour's pay.
   - Describe products and services fully.

- Be forthcoming about any limitations of data, software, assumptions, models, methods, and analysis.

III. Obligations to Colleagues and the Profession

The GIS professional recognizes the value of being part of a community of other professionals. Together, we support each other and add to the stature of the field. Therefore, the GIS professional will:

1. **Respect the Work of Others.**
   - Cite the work of others whenever possible and appropriate.
   - Honor the intellectual property rights of others. This includes their rights in software and data.
   - Accept and provide fair critical comments on professional work.
   - Recognize the limitations of one's own knowledge and skills and recognize and use the skills of other professionals as needed. This includes both those in other disciplines and GIS professionals with deeper skills in critical sub-areas of the field.
   - Work respectfully and capably with others in GIS and other disciplines.
   - Respect existing working relationships between others, including employer/employee and contractor/client relationships.
   - Deal honestly and fairly with prospective employees, contractors, and vendors.
2. **Contribute to the Discipline to the Extent Possible**
   - Publish results so others can learn about them.
   - Volunteer time to professional educational and organizational efforts: local, national, or global.
   - Support individual colleagues in their professional development. Special attention should be given to underrepresented groups whose diverse backgrounds will add to the strength of the profession.

IV. Obligations to Individuals in Society

The GIS professional recognizes the impact of his or her work on individual people and will strive to avoid harm to them. Therefore, the GIS professional will:

1. **Respect Privacy**
   - Protect individual privacy, especially about sensitive information.
   - Be especially careful with new information discovered about an individual through GIS-based manipulations (such as geocoding) or the combination of two or more databases.
2. **Respect Individuals**
   - Encourage individual autonomy. For example, allow individuals to withhold consent from being added to a database, correct information about themselves in a database, and remove themselves from a database.
   - Avoid undue intrusions into the lives of individuals.
   - Be truthful when disclosing information about an individual.
   - Treat all individuals equally, without regard to race, gender, or other personal characteristic not related to the task at hand.

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Appendix C: Ethics Guidelines for Trustworthy AI (Reduced)

Four Ethical Principles

I. Respect for human autonomy
II. Prevention of harm
III. Fairness
IV. Explicability

Seven Key Requirements

1. **Human agency and oversight**
   Including fundamental rights, human agency and human oversight
2. **Technical robustness and safety**
   Including resilience to attack and security, fall back plan and general safety, accuracy, reliability and reproducibility
3. **Privacy and data governance**
   Including respect for privacy, quality and integrity of data, and access to data
4. **Transparency**
   Including traceability, explainability and communication
5. **Diversity, non-discrimination and fairness**
   Including the avoidance of unfair bias, accessibility and universal design, and stakeholder participation
6. **Societal and environmental wellbeing**
   Including sustainability and environmental friendliness, social impact, society and democracy
7. **Accountability**
   Including auditability, minimisation and reporting of negative impact, trade-offs and redress.

The complete guidelines can be found under the following link:
https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai