Fanjingshan National Nature Reserve China

ΕΛΛΗΝΙΚΗ ΕΠΙΣΤΗΜΟΝΙΚΗ ΕΤΑΙΡΕΙΑ ΕΔΑΦΟΜΗΧΑΝΙΚΗΣ & ΓΕΩΤΕΧΝΙΚΗΣ ΜΗΧΑΝΙΚΗΣ

Τα Νέα της Ε Ε Ε Ε Γ Μ

162

Αρ. 162 – ΑΠΡΙΛΙΟΣ 2022

Guizhou, China

SIMSG ISSMGE

ISRM

ISSN: 2732-7248

ΠΕΡΙΕΧΟΜΕΝΑ

Shilin Stone Forest China

ΑΡΘΡΑ

Future of geotechnics: Disrupting tunnelling

The engineers behind the new Hypertunnel method aim to shake up the tunnelling status quo.

Underground construction innovations through the ages range from drill and blast – introduced to mining in the 1600s – to Marc Brunel's tunnelling shield used to build the Thames Tunnel between 1825 and 1843.

This was followed by the introduction of mechanical tunnelling machines, and, roughly a century later in the 1950s, an early version of the modern tunnel boring machine (TBM).

TBMs and tunnelling technologies have continued to evolve since then, most recently with the introduction of greater automation and digitalisation.

Nonetheless, TBMs have a reputation for being big and slow. The first two TBMs working on High Speed 2's Chiltern tunnels, for example, are 170m long and weigh 2,000t each. They advance at around 15m per day.

High tunnelling costs are also linked to the size and speed of the machinery.

This has prompted the likes of Tesla head Elon Musk to promise a tenfold acceleration of tunnelling with the help of new technology.

According to the website for Musk's Boring Company, its latest TBM, the *Prufrock*, is designed to launch from the surface and tunnel at more than 1.6km per week by using a continuous mining method.

But even Musk's approach is simply a further iteration of the current TBM.

Last year, UK start-up company Hypertunnel started making waves when it unveiled a system it believes could revolutionise tunnel building.

Hypertunnel director of engineering Patrick Lane-Nott says: "The reality is that while tunnelling has seen iterative development since the first boring machine came to the fore, the fundamentals of the actual method haven't changed.

"We believe that there are some real opportunities to grasp some of the technologies that are readily available today, but currently being used in other industries, to help boost and improve the overall tunnelling process."

These include horizontal directional drilling, underground surveying, digital twins, artificial intelligence, swarm robotics, 3D printing, dragline and autonomous technologies.

A combination of these forms the new Hypertunnel approach.

Entering hyper tunnelling

The onsite Hypertunnel process begins with the drilling of index bores to produce core samples along the entire tunnel path.

The horizontal directional drilling method used for this is a well known trenchless technique for installing pipelines and utilities. This technology can drill up to around 1.3m diameter, 4km long tunnels.

Instead of geotechnical investigations undertaken from the surface, the Hypertunnel approach aims to get a detailed picture of the geology and ground conditions from within the ground itself.

"What we propose is a much more detailed evaluation of the ground that we're going to work on," says Lane-Nott.

The preparation process includes the drilling of index bores along the entire tunnel path to produce core samples

In addition to geological maps and records, the traditional method of investigating a tunnel alignment would include drilling vertical boreholes at specific intervals along the tunnel route.

"Anecdotally those can be half a kilometre apart and you're just guessing what's happening between them," Lane-Nott adds.

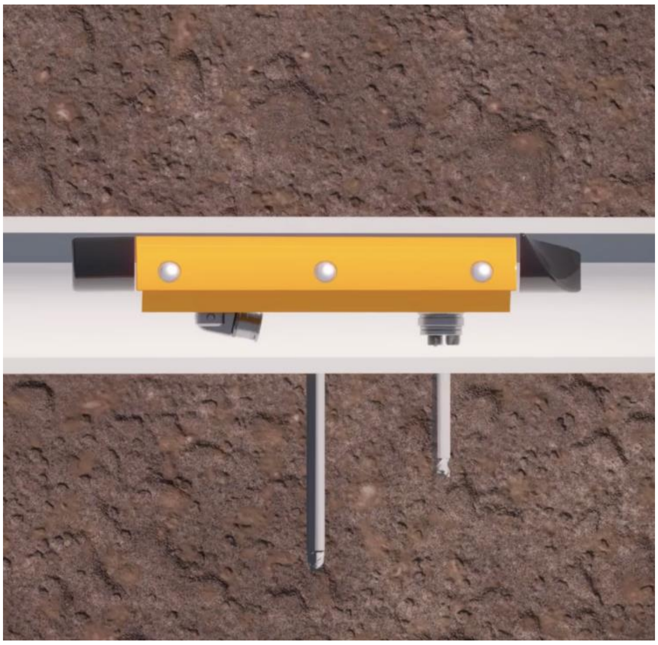
"You have to interpolate between those points to be able to guess what's going on in the geology. We think that brings a lot of risk. Your geology can change millimetre by millimetre through the tunnel path. We want to know exactly what's going on at any point.

"We want to take a complete bore sample down the whole length of the tunnel. The technology is readily available and used in the oil and gas industry.

"We can then put that information into our digital twin."

The next step involves drilling a series of bore pipes to form the outline or shell of the tunnel, in the same way as the original index bores.

These bores are then lined with 280mm high-density polyethylene pipes that create a "clean environment" and offer access for geological survey tools, including ground penetrating radar and seismic sensors.



The semi-autonomous Hyperbots are sent into the bore pipes to do most of the "dirty" work

Hypertunnel's robotic delivery system – a "swarm" of small, semi-autonomous robots similar to drones – is then put into action to help gather this information. These "Hyperbots" can be kitted out with different tools for different functions, including a "Hyperbit" for drilling.

The data is used to further enhance the 3D model – or digital twin – of the tunnel, which is created with the help of artificial intelligence and which supports building information modelling. The model will also detail the types of construction chemicals needed to stabilise the ground around the tunnel.

In the construction phase, the Hyperbots are once again sent into the "botways" carrying cartridges of construction chemicals. They build the tunnel using the additive manufacturing process familiar from 3D printing. The bots move around like the head of a 3D printer and can place construction materials to form the tunnel structure. This could also be done through permeation grouting and general ground consolidation methods.

The geological survey tools will then be sent inside the tunnel structure once more to make sure it has the correct thickness and strength.

"Once we're confident we've got our tunnel structure right, it is then about disrupting the unconsolidated ground that's inside it," says Lane-Nott.

"We then return to our index bores, those initial bores where we've taken our core samples from. They are also lined at this stage because we've done surveys through that as part of our initial data gathering surveying phase. We then use horizontal directional drilling techniques to ream out those pipes.

"That technique again is very well established; that's how they put large pipes into the ground using HDD [horizontal directional drilling].

"And what that does is that it creates space within the confinement of the tunnel structure where all of the unconsolidated ground is sitting, which then starts to collapse and to fall in."

Once the outline of the tunnel has been created by drilling bore pipes and 3D printing in the ground, the initial index bores are reamed out

To help this process Hypertunnel is exploring several techniques for specific geologies. These include sonic, dewatering and hydraulic fracturing.

"Once the ground has collapsed into a slump, then we can go in and just excavate that," Lane-Nott continues.

"We can deploy our dragline shield, which borrows technology from opencast mining where you have dragline buckets pulled around by cables that can pick up and scoop hundreds of tonnes in a single sweep."

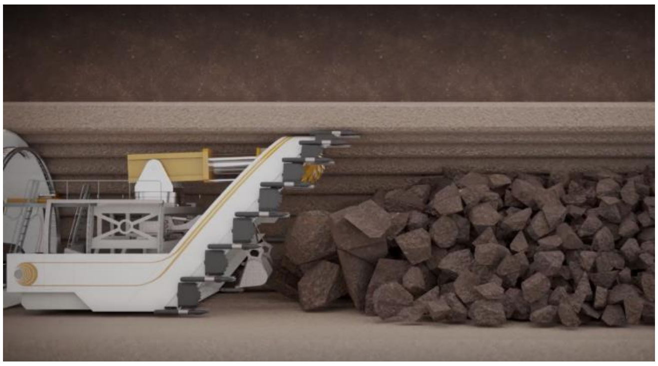
By running cables through the insitu pipes, the shield would be dragged through the tunnel to pick up all the spoil and finish off any lining needed on the inside.

The spoil can also be extracted to the surface, borrowing techniques from mining, where conveyors and nowadays autonomous trucks are used to move material.

Looking to the future

A key element of the Hypertunnel process is that people will not enter the tunnel environment or go near the cutting face during the construction or excavation phases.

"When the Victorians were building these amazing tunnels that we're still using today, they realised that the way to get those built quickly was to use lots and lots of people. So, they used to throw people at the problem, because they were not only cheap to employ, but the value of life in those days was not what it is now," says Lane-Nott.



After the geology within the shell is disrupted, spoil is removed with a remote-controlled excavation shield

“By taking some of those cues from the Victorians, who were using a ‘human swarm’, we can use the bots to do all the sort of nasty, dirty work that’s potentially dangerous. We can keep the humans out of the perilous area until we’ve got a full structure.”

Lane-Nott sees this as the underground construction method of the future, as he believes the benefits go beyond safety and efficiency.

“It’s a bit like keyhole surgery. We’re only using material as and when we need to, so that way we can be much more efficient with the amounts of material. And there’s a lot less transport and manoeuvring of all the different elements of it, because we’re building and using it insitu,” he says.

“From an environmental perspective, when we’re excavating our spoil, we take it out as it comes out of the ground.

“We don’t have to pulverise it into a dust, suspend it in a fluid, move it away from the face, and then have to post process it to be able to dispose of it. We can just utilise it in local civil work, for example.”

Hypertunnel is carrying out various studies into the use of its technologies, including working with Network Rail to use some of the elements to repair its tunnels.

But the real test will be with the first pilot tunnelling project that uses the approach from start to finish. The company is talking to a number of potential partners and sites for this trial, which could take place in the next six to 12 months.

(Nia Kajastie / GROUND ENGINEERING, 05 April, 2022, https://www.geplus.co.uk/features/future-of-geotechnics-disrupting-tunnelling-05-04-2022)

All About Offshore Wind Turbine Foundations

Net Zero Goals

The COP26 global summit in late 2021 made important progress in a number of areas. Countries worked toward the aim of closing the gap, limiting global warming to 1.5 deg C. Bold collective commitments were made to:

- Curb methane emissions
- Halt and reverse forest loss
- Align the finance sector with net zero emissions (carbon-neutral) by 2050
- Ditch the internal combustion engine
- Accelerate the phase-out of coal
- End international financing for fossil fuels

Many countries pledged to achieve net zero by the middle of the century. To achieve this goal, plans have been made to adjust the energy mix with a strong focus on clean energy. Renewable sources such as solar, wind, and hydrogen play an important role in reaching net zero.

The Growth of Offshore Wind

In regards to wind energy, the **onshore** wind industry has grown for decades and has been adapted by many countries around the world. The **offshore** wind industry is relatively newer; however, it has witnessed rapid expansion in the United States, Europe, and Asia in recent years. Furthermore, the cost of offshore wind has fallen dramatically, and it is speculated that this will become the cheapest form of energy in the industrialized world.

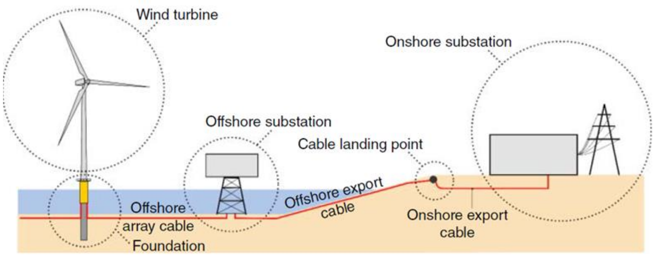


Figure 1: Typical layout of an offshore wind infrastructure connecting to the onshore transmission grid.

Figure 2 from the GWEC 2021 report shows the constant compound annual growth rate of 11% from the wind energy since 2015. The new installation of offshore wind has increased year-on-year, with 35GW additional capacity seen in 2020.

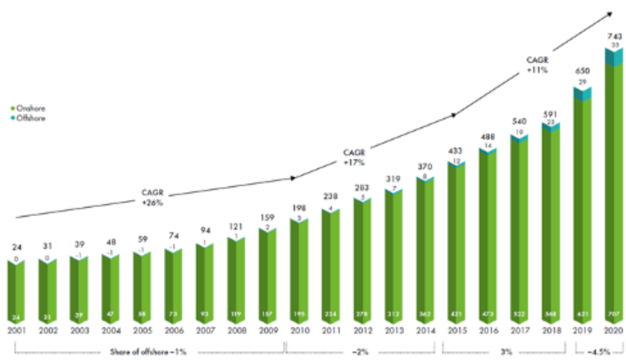


Figure 2: Global CAGR of wind energy (GWEC 2021).

The US Department of Energy, in its recent market report, showed an overview of the already announced offshore wind projects around the world mounting up to 29GW of new capacity in 2026. China reached its highest annual addition in 2021, while the United States, United Kingdom, Poland, and the rest of Asia expect exponential growth of new installations in the next five years.

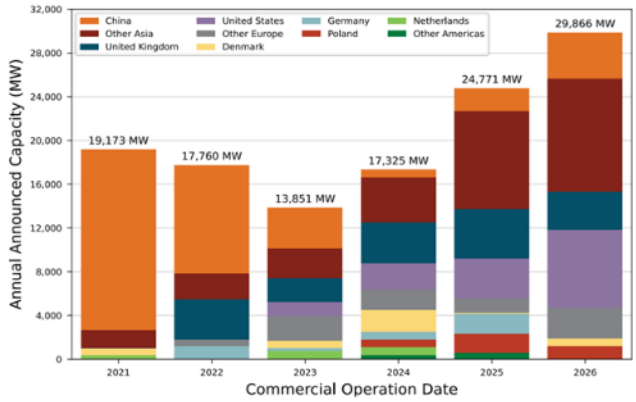


Figure 3: Offshore Wind Developer-announced COD.

The huge demand in capacity has also led to growing individual turbine capacity and larger rotor blades. It is expected that by 2035, the turbine capacity could reach 17MW, at the height of 495ft above sea level and rotor blades sweeping an area with 820ft in diameter.

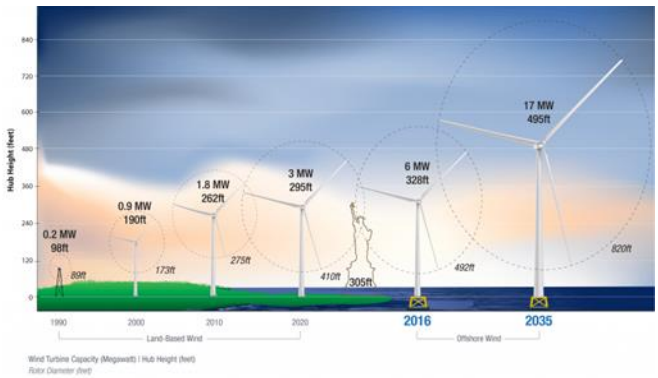


Figure 4: Sizes of wind turbine structures.

Types of Offshore Wind Turbine Foundations

Foundation selection for these offshore structures plays an important role in the overall concept design for offshore wind farms. There are significant financial implications attached to the choices that are made. Typically, foundations account for 16 to 34% of the overall costs, depending on the location and size of the wind farm.

Due to the vast size of a wind farm, there will be varying seabed conditions, including water depth and distance from the shore. As a result, the loads on the foundations will change, and ideally, the best design will be to design each foundation individually, which will give rise to a customized foundation design for each turbine location. However, from an economic point of view, it is desirable to use just a few foundation types to reduce costs and improve efficiency because the process of fabrication and installation can be carried out using the same installation vessel. Most North European developers prefer one type of foundation (either monopiles or jackets) in a site. This consideration often dictates the layout of the farm to avoid deeper water or soft, locally available mud.

In addition, many other aspects must be considered while choosing and designing the foundation for a particular site. They include:

- Ease to install under most weather conditions
- Varying seabed conditions
- Aspects of installation including vessels and equipment required
- Local environmental regulations (noise)

A general guide to foundation types in terms of water depth could be described as follows:

- Typically, for near-shore areas where WD is less than 30m, a **monopile foundation** would be the suitable and economical choice
- Going further and deeper up to 60m WD, **jacket structures on suction buckets or pile foundations** would be appropriate
- Deeper than 60m is the playing field of **regular offshore floating systems**, such as tension leg platform, spar, or semi-submersible

Each of the foundation types poses different sets of technical challenges.

Fixed foundations need to address concerns of:

- Pile design to withstand environment and dynamic loads from turbine
- Multiple seabed design conditions covering the wind farm, loadout, and installation

Floating foundations should be designed for:

- Safe operation under extreme pitch, roll, and heave wave motions
- Stability design and dynamic coupling of translational and rotational platform motions and turbine motions
- Dynamic behavior of mooring lines
- Buoyancy to support full weight of turbine, tower, and platform
- Anchoring system, mooring, ballast, and buoyancy factors dependent on spar, TLP, or semi-sub

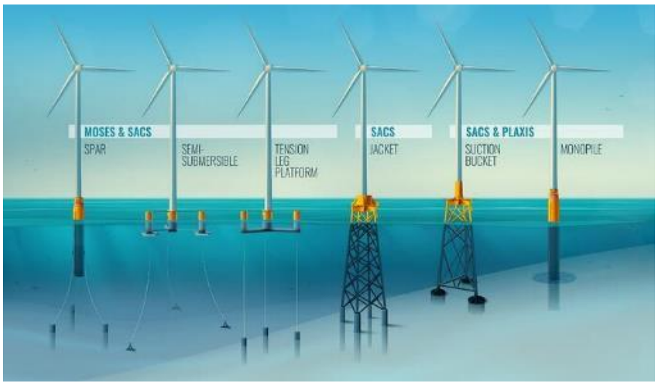


Figure 5: Types of wind turbine foundations, and Bentley software to address each type of foundation.

Foundation Design for Offshore Wind Turbines

The design of offshore wind structures found its origin in following the design of offshore oil and gas structures. The aim of the foundation is to transfer the loads of the substructure and superstructure safely to the ground. The loads on the foundation depend on the foundation system.

While the experience gained from offshore oil and gas operations can be applied, it is important to highlight the significant differences between these two types of structures. These differences deserve special attention. It is now widely acknowledged that offshore wind turbine structures are unique in their features. The most important difference with respect to oil and gas installations is found in large-scale offshore wind turbine structures where a heavy rotating mass is placed at the top of the slender tower. Offshore wind turbine structures are dynamically sensitive, because the natural frequencies of these slender structures are very close to the excitation frequencies imposed by the environmental and mechanical loads.

For typical 3.6MW turbines, the first natural frequency (eigen frequency) of the whole system is close to 0.3 Hz and for the corresponding 8MW turbine is 0.22 Hz. The frequency of the rotor of the wind turbine is in the range of 0.2 Hz. Typical wind turbine blades weigh 30t, and as a result, 90t is rotating at the top of the tower. On the other hand, the natural frequencies of offshore oil and gas platforms are more than 0.6 Hz and the most important cyclic/dynamic loading is the wave having frequencies 0.1 Hz (typical North Sea value). The forcing frequencies are not very close to the natural frequencies, making oil and gas platforms less sensitive to dynamics. (*Bhattacharya, 2019, Design of Foundations for Offshore Wind Turbines.*)

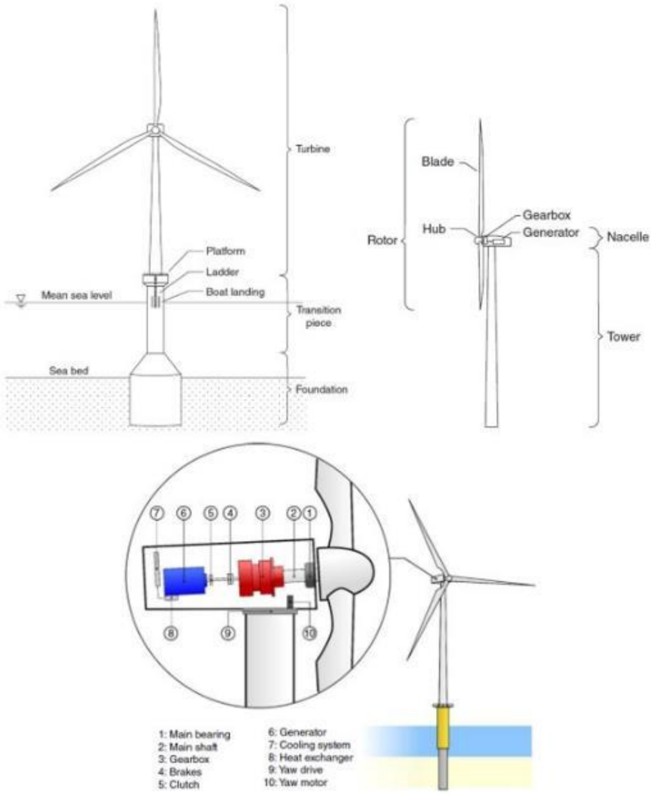


Figure 6: Typical components of an offshore wind structure with monopile foundation.

Figure 6 shows a typical monopile-supported wind turbine and a pile-supported fixed offshore jacket structure. It is very clear that the ratio of horizontal load to vertical load is very high in offshore wind turbines when compared with fixed-jacket structures. As a result, the monopile is a moment-resisting foundation.

Let's compare the single large-diameter monopile and multiple piles supporting a jacket in the load transfer mechanism. In the case of monopile-supported wind turbine structures, the load transfer is mainly through overturning moments, where the monopile/foundation transfers loads to the surrounding soil, and therefore there is lateral foundation–soil interaction. On the other hand, for a multiple support structure, the load transfer is mainly through push-pull action – i.e., axial load, as illustrated in Figure 7.

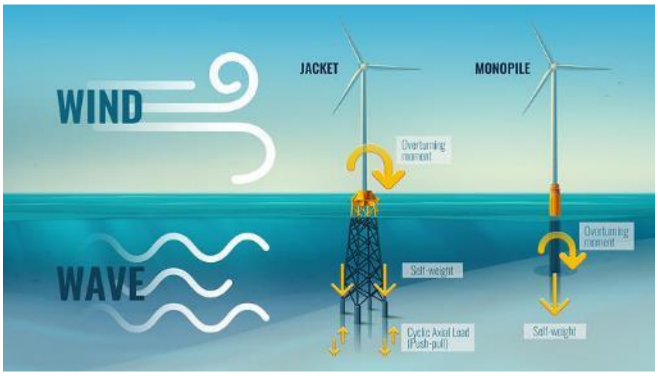


Figure 7: Load transfer mechanism for monopile and jacket on piles.

Next let's look at a particular type of floating system known as spar-supported floating offshore wind turbines with catenary mooring and suction caisson anchors. This is effectively the example of the Hywind concept, the first floating offshore wind farm. For foundation design, it is necessary to estimate an upper bound for the ultimate load on the anchor.

This can be obtained by taking the configuration where the mooring line is completely stretched and there is no part of it lying on the seabed. This is very similar to the configuration of a single taut mooring line. In this case, the load is transferred directly to the anchor without the effect of soil friction on a horizontal section of the mooring line.

Furthermore, in this configuration, the angle of the mooring line at the seabed is also maximal, which impacts the inverse catenary shape at the anchor. This scenario is unlikely to happen to a floating oil and gas platform on mooring.

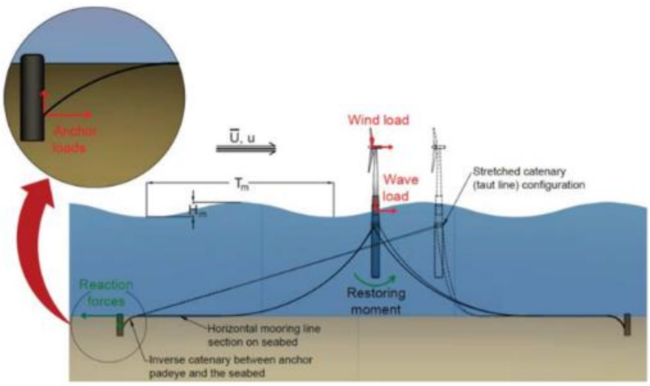


Figure 8: Load transfer for floating wind turbine systems (Bhattacharya).

Offshore wind foundation design also has to deal with the most complicated set of loadings on an offshore structure. DNVGL-ST-0437 (Loads and Site Condition for Wind Turbines) requires the structure to be designed for ultimate and fatigue strength of structural members and time history analysis shall be used for dynamic problems of a non-linear nature.

Following are the loadings to be considered for offshore wind turbine design:

- Operational loads as the result from the operation and control of the wind turbine
- Inertia and gravitational loads (static and dynamic loads) acting on the wind turbine, resulting from vibration, rotation, gravity, and seismic activity
- Aerodynamic loads caused by the airflow and its interaction with the stationary and moving parts of wind turbines
- Hydrodynamic loads caused by the water flow and its interaction with the foundation structures (including wave loads, breaking wave loads, and sea current loads)
- Hydrostatic loads which may be applicable for hull-type structures, such as semi-sub
- Sea ice loads
- Seismic loads
- Boat impact loads

The load time series for the offshore wind turbine combining all the above external conditions are required. This means thousands of load cases are to be checked.

A typical Fatigue Limit State (FLS) design would involve 5,000 to 10,000 dynamic force time history analysis simulations, while typical Ultimate Limit State (ULS) design involves 10,000 to 15,000 dynamic force time analysis simulations. Each time history simulation can be 600 seconds long after the initialization of transient with analysis increment of 0.05 to 0.01 seconds. So typically there are 12,000 to 60,000 load cases to be solved for each simulation. This leads to a huge challenge of data generation of input files and directory structure for thousands of dynamic time history load cases. This process is both time-consuming and error-prone.

Bentley's OpenWindPower software offers a complete engineering tool for designing both fixed foundations and floating platforms for offshore wind turbines. Read more about OpenWindPower, the industry-leading engineering tool for offshore structure analysis.

(Minh Pham / Virtuosity Blog, Apr 12, 2022, https://blog.virtuosity.com/all-about-offshore-wind-turbine-foundations)

Huge volcanic landslide identified on Santorini, Greece

Traces of the largest known volcanic landslide in the entire Mediterranean, with a volume of up to 125 cubic kilometers, have been discovered in the sea around the island of Santorini by Greek and foreign scientists.

The researchers' new study, which was published in the international geosciences Basin Research journal, says that based on the abundant evidence left behind, experts can estimate that the landslide occurred some 700,000 years ago.

Santorini is where one of the world's largest known eruptions of the last 12,000 years took place; it was during the Minoan era about 3,600 years ago.

Throughout its history, the island has experienced large explosions, caldera collapses and extensive lava formations.

However, significant landslides, in which large amounts of sediment and rocks slide into the sea and can cause tsunamis, had been almost unknown – until now.

(ekathimerini, 17.04.2022, https://www.ekathimerini.com/culture/1182403/huge-volcanic-landslide-identified-on-santorini/

The Hidden Giant: How a rift pulse triggered a cascade of sector collapses and voluminous secondary mass-transport events in the early evolution of Santorini

Jonas Preine, Jens Karstens, Christian Hübscher, Gareth J. Crutchley, Timothy H. Druitt, Florian Schmid, Paraskevi Nomikou

Abstract

Volcanic island sector collapses have the potential to trigger devastating tsunamis and volcanic eruptions that threaten coastal communities and infrastructure. Considered one of the most hazardous volcano-tectonic regions in the world, the Christiana-Santorini-Kolumbo Volcanic Field (CSKVF) lies in the South Aegean Sea in an active rift zone. Previous studies identified an enigmatic voluminous mass-transport deposit west and east of Santorini emplaced during the early evolution of the edifice. However, the distribution and volume as well as the nature and emplacement dynamics of this deposit remained unknown up to now. In this study, we use an extensive dataset of high-resolution seismic profiles to unravel the distribution and internal architecture of this deposit. We show that it is located in all basins surrounding Santorini and has a bulk volume of up to 125 km^3, thus representing the largest known volcanic island mass-transport deposit in the entire Mediterranean Sea. We propose that the deposit is the result of a complex geohazard cascade that was initiated by an intensive rift pulse. This rifting event triggered a series of smaller precursory mass-transport events before large-scale sector collapses occurred on the northeastern flank of the extinct Christiana Volcano and on the southeastern flank of the nascent Santorini. This was followed by the emplacement of large-scale secondary sediment failures on the slopes of Santorini, which transitioned into debris and turbidity flows that traveled far into the neighboring rift basins. Following this cascade, a distinct change in the volcanic behaviour of the CSKVF occurred, suggesting a close relationship between crustal extension, mass transport and volcanism. Cascading geohazards seem to be more common in the evolution of marine volcanic systems than previously appreciated. Wider awareness and a better understanding of cascading effects are crucial for more holistic hazard assessments.

Highlights

- We discover the deposits of a complex mass-wasting cascade around Santorini, located in the Aegean Sea.
- The cascade involved volcanic sector collapses and voluminous secondary sediment failures.
- We show that an intensive regional rift pulse is the most likely trigger for the mass-wasting cascade.
- The emplacement of the cascade marks a distinct shift in the behavior of the volcanic field.
- Our study highlights sensitive feedbacks between tectonics, mass-wasting and volcanism.

1 INTRODUCTION

Submarine landslides offshore volcanic islands are among the largest-volume mass movements on Earth's surface (Masson et al., 2002; Moore et al., 1994). Individual landslide deposits can contain hundreds to thousands of cubic kilometres of material extending over distances of hundreds of kilometres (Moore et al., 1989). These collapse events are capable of generating devastating tsunamis on oceanic scales (Løvholt et al., 2008) and the associated unloading of the volcanic systems may trigger explosive volcanic eruptions (Hunt et al., 2018; Siebert, 1984). In recent years, marine geophysical surveys have revealed that sector collapses around volcanic islands are a common and important process during the evolution of volcanic edifices, and might occur in complex disaster cascades involving volcanic eruptions, tsunamis and earthquakes (Hunt et al., 2018; Ida & Voight, 1995; Karstens et al., 2019; McGuire, 1996; Patrick et al., 2020; Voight, 2000; Watt et al., 2021). Understanding the origin, preconditions and triggers of volcanic sector collapses, as well as their emplacement dynamics in the marine realm, is crucial for determining the magnitude of associated tsunamis and their potential influence on local volcanic systems.

Given the complexity of submarine volcanic landslides, many questions remain open regarding potential trigger mechanisms, emplacement dynamics and the role of secondary failure processes. Recent studies have shown that landslide volumes are often much greater than the volume of the associated sector collapse scars, which implies significant incorporation of seafloor sediment into the mobilised volume (Karstens et al., 2019; Kühn et al., 2021; Watt et al., 2012, 2021). Watt et al. (2012) noted that many submarine landslide deposits from volcanic islands are characterised by a blocky-surfaced proximal part, which mainly comprises collapsed volcanic material, and a smoother-surfaced apron, which mainly comprises seafloor sediment. The entrainment of secondary sediment into volcanic landslides can be very widespread on low (<1°) gradients and may dominate the total landslide volume (Crutchley et al., 2013; Watt et al., 2012). At Ritter Island, for example, only 20% of the total volume that was deformed or mobilised as part of the collapse was derived from the rapid, tsunami-generating volcanic collapse (Karstens et al., 2019; Watt et al., 2019). Further, results from IODP Expedition 340 showed that the distal and medial parts of landslide deposits offshore Montserrat and Martinique lacked coarse and chaotic subaerial volcanic debris avalanche material, but comprised turbidites and hemipelagic deposits derived from secondary sediment failures (Brunet et al., 2016; Le Friant et al., 2015, 2019).

To explain the occurrence of such voluminous secondary sediment failures at volcanic islands, it has been proposed that the rapid emplacement of failed volcanic edifice material initiates the propagation of a décollement, which causes widespread failure of pre-existing low-gradient seafloor sediment (Watt et al., 2012). According to this model, the load imposed by the initial failure may generate excess pore fluid pressure and trigger additional sediment failures in slope and basin areas that would not otherwise be prone to failure (Le Friant et al., 2015, 2019; Viesca & Rice, 2012). These results have important implications for the magnitude of tsunami generation by volcanic island landslides since secondary seafloor sediment failures are likely to be much less tsunamigenic than the proximal, block-rich, mass flows (Le Friant et al., 2019; Watt et al., 2012). Therefore, the complexities within submarine volcanic landslides must be carefully considered for an accurate assessment of associated hazards (Watt et al., 2021).

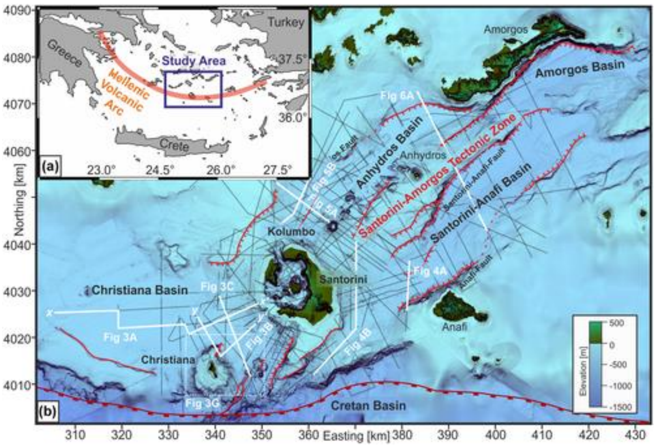


FIGURE 1

(a) Regional setting of the Southern Aegean Sea, showing the Hellenic Volcanic Arc and the study area (blue box). (b) Morphological map of the CSKVF showing islands, basins, volcanic centres and major extensional structures (red lines) after Nomikou, Hübscher, et al. (2016), Nomikou et al. (2018), Nomikou Hübscher et al. (2019). Coordinate system is UTM Zone 35N, WGS84. Grey lines show all seismic profiles, white lines indicate the locations of seismic profiles shown in this study. Dashed white rectangle indicates the location of the 3D view of Christiana shown in Figure 3(g). Bathymetry from Nomikou et al. (2012, 2013, 2018, 2019) and Hooft et al. (2017). Topography from the Hellenic Military Geographic Service (HMGS)

Although volcanic sector collapses are fairly common in the evolution of volcanic edifices, systematic surveys of their remnants are only available for a small number of volcanic island groups and arcs (Watt et al., 2021). Examples from the Hellenic Volcanic Arc in the densely populated Aegean Sea are sparse despite the known occurrence of large-scale volcanic centres and enhanced seismicity, which make this arc one of the major risk factors for the eastern Mediterranean (Sørensen et al., 2012). Preine et al. (2022) reported a large mass-transport deposit within the Christiana-Santorini-Kolumbo volcanic field (CSKVF) in the central Aegean Sea. Chrono-stratigraphic relationships indicate that the deposit was emplaced during the early evolution of Santorini, approximately 0.7 Myrs ago (Preine et al., 2022). However, the distribution, volume, trigger mechanisms and emplacement dynamics of the deposit have not been investigated so far.

Since 2006, we have compiled a comprehensive dataset of more than 3,200 km of high-resolution multi- and single-channel seismic reflection data (Hübscher et al., 2006; Karstens et al., 2020; Sigurdsson et al., 2006) covering the entire basin system adjacent to Santorini (Figure 1b). Using this extensive dataset, the first objective of this study is to map the distribution of the large mass-transport deposit (MTD) and estimate its volume. Our second objective is to investigate the nature of this deposit and identify kinematic indicators to determine potential sources. The third objective of this study is to reconstruct its emplacement dynamics, analyse cascading effects, assess its impact on the shallow volcanic plumbing system of the CSKVF and discuss implications for geohazard assessment.

2 GEOLOGICAL FRAMEWORK

The marine CSKVF is one of the most hazardous volcano-tectonic fields in the world (Druitt et al., 1999). It is located on the Hellenic Volcanic Arc, which stretches from Greece in the west towards Turkey in the east and was formed as a consequence of the subduction of the Nubian underneath the Eurasian Plate (Figure 1a) (Le Pichon & Angelier, 1981). Having produced over 100 explosive eruptions including at least four caldera collapses during the last 360,000 years, the CSKVF poses a major threat (eruptions, tsunamis, earthquakes) to the eastern Mediterranean region (Druitt et al., 1999; Kutterolf et al., 2021a, 2021b; Nomikou, Druitt, et al., 2016; Satow et al., 2021). The iconic Minoan Eruption ~3,600 years before present may have contributed to the fall of the great Minoan civilisation, leaving its imprint on Greek mythology, archeology and volcanology (Druitt et al., 2019).

Situated on highly stretched continental crust in an SW-NE oriented rift zone, the CSKVF comprises the extinct Christiana Volcano, the Santorini Caldera, the polygenetic submarine Kolumbo Volcano, as well as the Kolumbo Volcanic Chain (Figure 1b) (Hooft et al., 2017, 2019; Hübscher et al., 2015; Nomikou et al., 2012, 2013; Preine et al., 2022). The CSKVF is located on the junction of the broad Christiana Basin to the West and the complex Santorini-Amorgos Tectonic Zone (SATZ) to the East (Figure 1b) (Nomikou et al., 2018, 2019). The Christiana Basin has been named after the Christiana Islands, a group of three highly eroded volcanic islets belonging to the same submarine edifice southwest of Santorini (Figures 1b and 3g), which is assumed to have been dormant since the Early Pleistocene (Preine et al., 2022). There are three larger volcanic domes (200–300 m volcanic relief) east of Christiana, which are partially cut by SW-NE trending faults (Nomikou et al., 2013). As a zone of SW-NE trending rifts, the SATZ extends from the eastern flank of Santorini towards Amorgos and separates the Cycladic Plateau to the northwest from the minor Anafi-Astypalaea Plateau to the southeast (Nomikou et al., 2018, 2019). These complex tectonic horst and graben segments evolved during four major tectonic pulses and are bordered by SW-NE trending active extensional to transtensional faults (Hooft et al., 2017; Hübscher et al., 2015; Nomikou et al., 2016, 2018; Preine et al., 2020).

Besides the occurrence of pyroclastic-flow deposits from the recent (<0.36 Ma) eruptions of Santorini forming the Thera Pyroclastic Formation (Hübscher et al., 2015; Preine et al., 2022; Sigurdsson et al., 2006), the literature of major MTDs from the basins surrounding the centres of the CSKVF is surprisingly sparse given the long history of volcanic build-up, caldera-collapse and enhanced tectonic exposure (Bohnhoff et al., 2006; Nomikou et al., 2018; Preine et al., 2020). Bell et al. (2013) reported a surficial landslide deposit on the southeastern flank of Santorini, which contained large remobilised blocks composed of pyroclastic-flow deposits from the Minoan eruption. These authors proposed that this deposit is the result of a landslide that was triggered by a large seismic event after the Minoan eruption (Bell et al., 2013). Tsampouraki-Kraounaki and Sakellariou (2018) reported several chaotic seismic units in the Christiana Basin, including a particularly thick (>100 ms two-way traveltime (TWT)), transparent unit, which thickens towards Santorini and was interpreted to be of pyroclastic origin that might have been related to an eruption in the early phase of the evolution of Santorini. In a recent study, however, it was shown that this deposit also occurs in the Anhydros Basin on the eastern side of Santorini and that the internal architecture is also con-sistent with that of a large MTD (Preine et al., 2022). This deposit was emplaced after volcanism aligned southwest and northeast of Santorini, but before the emergence of enhanced, rift-wide volcanism (~0.7–0.36 Ma) and the onset of the explosive Thera Pyroclastic Formation (<0.36 Ma; Preine et al., 2022).

…

6 CONCLUSIONS

The analysis of an extensive 2D seismic dataset from the Christiana-Santorini-Kolumbo Volcanic Field has allowed us to identify and map the largest volcanic island mass-transport deposit from the Mediterranean Sea, which occurred in the early phase of the evolution of Santorini ~0.7 Myrs ago. Our results show that emplacement of the Santorini Mass-Transport Deposit (SMTD) likely proceeded as a complex multi-stage cascade, which occurred in all basins surrounding Santorini. We identify five processes that might have contributed to the SMTD cascade: rifting, precursory mass-transport events, catastrophic collapses, secondary sediment failures and debris flow deposition. Our interpretation is that the emplacement of the SMTD was initiated by an intensive rift pulse, which occurred along SW-NE-directed faults extending from the Christiana Volcano in the southwest towards the island of Amorgos in the northeast (Figure 11a). Smaller precursory mass-transport events took place before catastrophic frontally confined sector collapses occurred at the northeast flank of the Christiana Volcano and on the southeastern flank of proto-Santorini (Figure 11b). As a consequence, significant secondary sediment failures on the slopes of proto-Santorini were triggered. These secondary sediment failures are frontally emergent and transitioned into debris flows and turbidity flows that transported large amounts of sediment towards the rift basins northeast of Santorini (Figure 11c). Constituting by far the largest portion of the entire SMTD sequence (>90%), these secondary failures are additional evidence for the importance of secondary processes in the emplacement of mass movements around volcanic islands, and they highlight the key role of reflection seismic surveys in providing detailed insights into such dynamics. The emplacement of the SMTD correlates with a transition from a phase of relative volcanic dormancy to a phase of basin-wide emergence of volcanoes, highlighting how closely volcanism, tectonism and mass-transport can interact in rift-hosted volcanic systems.

https://onlinelibrary.wiley.com/doi/full/10.1111/bre.12667

First published: 06 April 2022,
https://doi.org/10.1111/bre.12667

Introducing rainfall thresholds for landslide triggering based on artificial neural networks

Pierpaolo Distefano, David J. Peres, Pietro Scandura, and Antonino Cancelliere

Abstract

In this communication we show how the use of artificial neural networks (ANNs) can improve the performance of the rainfall thresholds for landslide early warning. Results for Sicily (Italy) show how performance of a traditional rainfall event duration and depth power law threshold, yielding a true skill statistic (TSS) of 0.50, can be improved by ANNs (TSS = 0.59). Then we show how ANNs allow other variables to be easily added, like peak rainfall intensity, with a further performance improvement (TSS = 0.66). This may stimulate more research on the use of this powerful tool for deriving landslide early warning thresholds.

1 Introduction

Landslides triggered by rainfall can cause damage to infrastructure and buildings and, in the worst scenario, even lead to human losses (Froude and Petley, 2018). Commonly, rainfall thresholds indicating the conditions under which landslides can potentially occur are a key component of warning systems aimed at protecting the population from a possible landslide event. In most cases, thresholds are determined using empirical methods that link characteristics of precipitation, such as duration *D* and mean intensity *I* or rainfall depth, to landslide occurrence (Caine, 1980). Rainfall thresholds are usually determined by assuming a predetermined parametric equation, which in most cases is a power law (Guzzetti et al., 2008). In general, for a given set of predictors, the choice of a predetermined threshold equation form (e.g. power law) can potentially limit its performance because the informative content of the considered predictor variables may not be exploited to the fullest. This holds true all the more so when searching for alterative or additional variables with the aim of improving the performances of the thresholds, such as antecedent rainfall conditions (Glade et al., 2000), water storage, and soil moisture data (Bogaard and Greco, 2018; Marino et al., 2020). For the case of *E*–*D* or *I*–*D* thresholds the use of a power law is customary, and its rationale has also been verified based on a combined stochastic and physics-based approach (Peres and Cancelliere, 2014). In contrast, in the case of either a different pair of variables or the analysis of more than two variables, there is no analogous prominent parametric form of the threshold equation. For instance, as reported by Conrad et al. (2021), alternative formulas have been considered for hydrometeorological thresholds – i.e. based on rainfall and soil moisture or catchment storage – including linear and bilinear functions, interpolated line segments without a mathematical function, cut-off values for integration of antecedent conditions with traditional rainfall thresholds, and more complex logical operators. The use of predetermined parametric forms can finally jeopardise the scientific soundness of comparisons between thresholds using different sets of predictors (e.g. rainfall thresholds vs. thresholds using soil moisture). Artificial neural networks (ANNs), belonging to artificial intelligence or machine learning techniques, allow the mentioned limitation to potentially be removed as they are universal approximators, i.e. capable of reproducing any continuous function (Haykin, 1999).

Up to now, a number of studies have used the potentiality of ANNs and of other machine learning techniques in landslide analysis. Many studies focused on susceptibility mapping and individual slope instability have exploited the potentialities of ANNs (Reichenbach et al., 2018). In other studies, the focus is on the prediction of individual deep-seated landslide displacements by machine learning algorithms using detailed in situ data (e.g. van Natijne et al., 2020). Based on this briefly outlined state of the art, it appears that ANN skills are mainly used to create susceptibility maps and/or in local early warning systems, while application for territorial landslide early warning (Piciullo et al., 2018) has not been investigated so far. In this communication, we present our preliminary investigations showing how ANNs can allow landslide early warning thresholds to be derived with higher performances than traditional rainfall intensity–duration power law thresholds.

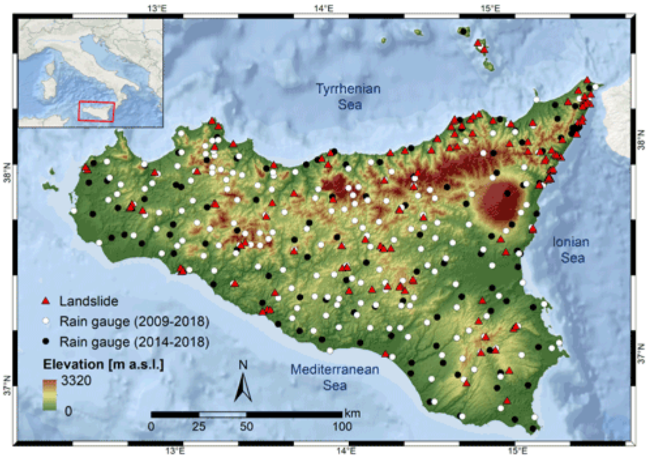


Figure 1 Elevation map showing location of landslides and rain gauges in Sicily considered in this study. The rainfall data set was built by joining data sets managed by different authorities and landslides from the FraneItalia inventory (Calvello and Pecoraro, 2018).

…

4 Concluding remarks

The identification of rainfall thresholds indicating landslide-triggering conditions is a key step for implementing territorial landslide early warning systems. Commonly, thresholds are searched in a limited space, i.e. constrained to a predetermined parametric form, which is generally a power law linking rainfall event, duration *D*, and mean intensity *I* (or total depth). In this communication we have shown that choosing a predetermined form for the law of the threshold can potentially limit the performance of the empirical model and how artificial neural networks are a valuable tool to overcome this limitation. The analysis, referring to the case study of Sicily, has shown that an *E*–*D* power law threshold has a maximum true skill statistic of $TSS = TSS_0 = 0.50$. On the other hand, the classifier based on neural networks, using the same pair of input variables, yielded a significantly greater TSS = 0.60. It has also been shown how neural networks allow the potential information content of other variables to be easily explored and hence provide a way to improve predictive performance. For instance, it has been shown that the inclusion of peak rainfall intensity as an additional variable can lead to an improvement of performance. It is important that when training neural networks, generalisation capabilities are ensured, for instance by the early-stopping technique. Overfitting is not an issue for the traditional approach based on the power law – or any other parametric equation – as in general the number of free parameters is very low (two for a power law). This may be a drawback for neural networks even though it forces one to consider both triggering and non-triggering events, which is fundamental for obtaining thresholds with acceptable statistical characteristics (Peres and Cancelliere, 2021). Another possible disadvantage of neural networks with respect to predetermined-form thresholds is also represented by the fact that it may be difficult to express the neural network classifier as a simple equation. This could limit the practical implementation of triggering thresholds based on neural networks, which could be perceived as impractical by practitioners. However, this limit can for instance be overcome by providing a user-friendly software to the end user.

Distefano, P., Peres, D. J., Scandura, P., and Cancelliere, A.: Brief communication: Introducing rainfall thresholds for landslide triggering based on artificial neural networks, Nat. Hazards Earth Syst. Sci., 22, 1151–1157, https://doi.org/10.5194/nhess-22-1151-2022

(Natural Hazards and Earth System Sciences / Brief communication, https://nhess.copernicus.org/articles/22/1151/2022/)

Prediction of Concrete Dam Deformation through the Combination of Machine Learning Models

Patricia Alocén, Miguel Á. Fernández-Centeno and Miguel Á. Toledo

Abstract

Dam safety monitoring is of vital importance, due to the high number of fatalities and large economic damage that a failure might imply. This, along with the evolution of artificial intelligence, has led to machine learning techniques being increasingly applied in this field. Many researchers have successfully trained models to predict dam behavior, but errors vary depending on the method used, meaning that the optimal model is not always the same over time. The main goal of this paper is to improve model precision by combining different models. Our research focuses on the comparison of two successful integration strategies in other areas: Stacking and Blending. The methodology was applied to the prediction of radial movements of an arch-gravity dam and was divided into two parts. First, we compared the usual method of estimating model errors and their hyperparameters, i.e., Random Cross Validation and Blocked Cross Validation. This aspect is relevant not only for the importance of robust estimates, but also because it is the source of the data sets used to train meta-learners. The second and main research topic of this paper was the comparison of combination strategies, for which two different types of tests were performed. The results obtained suggest that Blocked CV outperforms the random approach in robustness and that Stacking provides better predictions than Blending. The generalized linear meta-learners trained by the Stacking strategy achieved higher accuracy than the individual models in most cases.

Keywords: stacking; blending; combination; meta-learner; experts; machine learning; Cross Validation; radial displacement

1. Introduction and Background

Monitoring the safety status and behavior of dams plays a crucial role in civil engineering, due to the high cost that dam failure can entail. Monitoring techniques that comprise the safety system of a dam and its follow-up have evolved over time with technological advances, including artificial intelligence.

In recent years, the development of predictive models with machine learning techniques has been widely applied to different practical problems. Specifically, in the field of dam safety, the area of machine learning is attracting growing attention because of the complexity of the dam system, involving materials of great heterogeneity. Machine learning models achieve high accuracy in the prediction of their behavior, and a comparison with the measured responses allows early detection of anomalous behavior that may reveal an internal failure of the infrastructure. It is therefore of vital importance to achieve the highest possible accuracy with the trained models. From this derives the main objective of this research, which is to increase the accuracy of the usual models through their combination.

Many researchers have already successfully applied these techniques, including Support Vector Machine (SVM) [1], Boosted Regression Trees (BRT) [2], Random Forest (RF) [3], and different types of Neural Networks (NN) [4].

Fernando Salazar et al., for example, obtained promising results by applying these techniques to real cases in the field of dam safety. However, he emphasizes the need for further generalization and validation [4]. They successfully used BRT in several of their research studies [2,5,6]. Furthermore, they demonstrated the effectiveness of the mentioned techniques compared to the usual statistical models, concluding that BRT was the best model over 14 target variables [7]. Support Vector Regression can also be used as an accurate model to predict displacement of dams [8], while J. Mata demonstrates that Neural Networks have great potential for assessing dam behavior [9]. Herrera et al. compared Machine Learning models of different nature and managed to accurately predict hourly urban water demand [10]. Kang et al. also obtained good results using the Machine Learning RBFN technique [11].

These models, called experts or first-level models, do not perform in the same way in all periods of the series. Therefore, the possibility of finding different optimal experts depending on patterns arise. By combining those experts, a second-level machine learning model, or meta-learner, can identify such patterns and maximize accuracy, which leads us to the main topic of this paper: combination of models through Stacking and Blending.

Stacked generalization was introduced by Wolpert in 1992, where the first-level models are trained and later combined during the training of the meta-learner. The inputs of the meta-learner are the predictions of each of the experts generated during the Cross Validation (CV) process [12]. If all the available predictions are used to train the meta-learner, we speak of Stacking, while if only 10 or 20% of the data is used, we speak of Blending [13]. The training set used in Blending is called the Hold-out set.

Before detailing the main topic of this paper, we consider it necessary to emphasize the importance of the Cross Validation process and robust estimation, since the inputs of the second-level model of Stacking and Blending are derived from this process.

The usual division of the data set between training and validation allows for the evaluation of the models in the latter subset, which has a reduced percentage of inputs. For a more reliable and accurate estimation, the concept of Cross Validation is introduced.

This evaluation method consists of dividing the training set into folds (usually 10), where a model is iteratively trained with all folds except one, which is used for testing. This is repeated until all folds have been used for testing. Hence, all the examples of the training set are used for training and testing at least once. The estimated error is the average of the errors committed across these test folds.

In all machine learning problems, CV plays a fundamental role since it is used to estimate not only the error that the model will make on future data, but also the optimal hyperparameters of the model. For the research discussed in this paper, CV also plays an important role in the generation of the training set of the second-level model, which is explained in detail in Section 2. Therefore, we compare two types of CV to select the best process: Random or Blocked CV.

Random CV is the most common Cross Validation process and consists of dividing the training data set into folds whose records are chosen randomly. However, it is not the most appropriate option for practical problems where time dependence between instances is found, as in the case of dams. If Random CV is used in such problems, the error of the Random CV will be too optimistic (over-estimated error), giving very low errors during Cross Validation compared to the validation set. As Roberts et al. note, "The tendency for values of nearby observations to be more similar than distant observations is widespread, if not pervasive" [14], which implies an overly optimistic CV error.

To solve this problem, researchers, such as Bergmeir and Benítez, developed and used different types of CV. Among these methods lies the method based on the last block, used in some papers that will be mentioned below, and also the following methods: Cross Validation with omission of dependent data, where the dependent data are identified and excluded from the training set, and Cross Validation with blocked subsets, which is the CV proposed in this paper, where each fold corresponds to a year of the training set [15]. Although CV based on the last block is also appropriate, more weight should be given to the most recent estimated errors, since following a forward sequence, the fewer data there are, the higher the calculated error [2].

Roberts et al. demonstrate that Blocked CV generates a more robust error estimate than Random CV [14]. On the other hand, Bergmeir and Benítez do not find under- or over-estimated error when applying Random CV, although they recommend using Blocked CV together with an adequate stationarity control [15]. Regarding the research carried out by Herrera et al., the authors prefer a sequential CV as it is more similar to the original problem, where predictions are always made on data in ascending time order [10].

Few of the articles on the behavior of dams contain specific research on the CV employed. Some researchers use only one validation set to estimate the error [11] and emphasize that, if the conditions affecting the dam change, the model will perform poorly in future [4]. This hypothesis always contains some truth, but it is more reliable to give estimates of errors through Blocked CVs because it tests models considering more years. Some authors do not specify the type of CV used [5,7,8,9], while others divide the data set into training, validation (last two years available) and test (last year available) [3]. Fernando Salazar specified the processes used in two articles, using sequential CVs to estimate errors as averages of weights that decrease geometrically every year [2,6].

Since the movement cycle of the dam is annual, we decided to use Blocked CV, also called Annual CV, in this paper, where each block corresponds to a year. The predictions made, during the CV process of each year, are used to train the metalearner through Stacking and Blending.

The main interests in the comparison of Stacking and Blending strategies focus on computational cost reduction and error optimization. The development of engineering technology to collect data has led to a very large data set for modeling training, depending on the data collection period. Thus, the computational cost of model training increases. Efficiently decreasing the dimensions of the data set, while being able to maintain model accuracy, is fundamental. However, it is reasonable to expect that a model with more examples would be more accurate.

Regarding this matter, numerous articles have been published in several fields showing the successful results generated from combining experts by linear regression [13], or a multi-response model classifier [16]. These techniques have been applied not only in the scientific domain, but also in business. For instance, Netflix held a Kaggle (a subsidiary of Google LLC, it is an online community of data scientists and machine learning professionals) competition to develop an algorithm to predict user ratings for films, which was won by BellKor's Pragmatic Chaos team thanks to the combination of different experts.

The success of these strategies in other fields [13,17], together with their novelty, explains the interest in their application to the field of dam safety.

Research related to model combination for dam safety encompasses several approaches. Multi-model ensemble strategies using machine learning algorithms have been used to combine the inflow predictions of the Probability Distributed Model, Integrated Flood Analysis System, and Génie Rural à 4 paramètres Horaire models, and improve the accuracy of the predictions [18]. Other authors also use predictions from statistical and time series models as inputs to a second-level model trained by the Extreme Machine Learning algorithm [19], or induced ordered weighted averaging (IOWA) [20].

Other approaches that have been taken include the integration of models that attempt to predict parts of a series caused by external factors with models that attempt to predict the unknown [21,22].

On the other hand, Hong et al. were able to identify a pattern of behavior of two models (Random Forest and Gradient Boosting) to predict dam inflow, where one performed better than the other above a certain cutoff point [23]. However, for most dam problems, the detection of patterns among experts' performance is not straightforward and a more general solution is needed.

All these articles use statistical or time series models to train a second-level predictive model using machine learning algorithms, while we use the predictions of machine learning models as input. Moreover, none of the mentioned articles specifies whether the comparisons have been performed using Stacking or Blending. Our research is innovative because, to our knowledge, it is the first to introduce a combination of experts with these strategies to improve the precision of typical ML models used in the research of the existing literature.

Therefore, this study aims to improve the precision of first-level models by their combination through Stacking and Blending, and to broaden knowledge of both strategies in order to determine the best one. The algorithm chosen to perform such combinations is Generalized Linear Regression (GLM), due to its success in other fields. The selection of the best experts to use as input is made by the Akaike information criterion. We also analyze the differences between Random and Blocked CV.

…

4. Conclusions

We presented a methodology that successfully combined experts to improve the accuracy and robustness of a machine learning model of the movement of a concrete dam. This paper provides new insights into the optimal strategy for performing combinations in the field of dam behavior and security. Furthermore, we highlighted the importance of the appropriate choice of the type of Cross Validation process.

Blocked CV was preferable to Random CV to estimate the model error on future data. It was observed that Random CV generates an error estimator significantly different from that obtained in the validation set, with an average difference (Equation (5)) of −210.56%, presumably due to time dependence, which makes it an unreliable strategy. On the contrary, the differences (Equation (5)) regarding Blocked CV have a mean value of −8.23%, which is significantly lower than Random CV. The RMSE values in the validation set for both types of CV are similar. Regarding the training of experts through Blocked CV, we achieved models with good prediction accuracy for all target variables, with a $RMSE_{cv}$ of the optimal experts lying within the range of 1.288 mm and 2.018 mm.

Stacking was considered a better strategy than Blending, since clear dependence of the Blending model on the Hold-out set used in the training was observed, with a variance value of up to 0.868 in the case of pendulum 1. Since a model trained using the Blending strategy involves using 10% or 20% of the data, the model is subject to the peculiarities of the year used in its training. The results in Table 4 emphasized that, by changing the Hold-out set in blending, the RMSE committed in the validation set significantly varies, and is higher, on average, than when adopting the Stacking strategy.

Regarding the results obtained by training experts and meta-learners on different sets and validated over different years, it was noted that the Stacking meta-learner was more accurate in most cases (60% on average). Consequently, Stacking was considered a more robust strategy for training second-level models, presumably due to superiority in the number of instances used for training.

Finally, comparing the series of predictions of the meta-learner built by generalized linear regression and the optimal expert, the second-level model improves the accuracy of the best expert in all the pendulums, with improvement percentages of up to 14.8%. Only one exception is found where accuracy is almost identical. Future research should aim to train the meta-learner through different algorithms using the Stacking strategy to determine the best meta-learner algorithm.

As a global conclusion, a methodology is proposed in which experts of different natures are trained using Blocked CV combined with a Stacking strategy.

Water **2022**, *14*(7), 1133;
https://doi.org/10.3390/w14071133

https://www.mdpi.com/2073-4441/14/7/1133/htm

Time to rethink the scientific CV

Fresh formats showcase researchers' work more effectively.

Chris Woolston

New CVs formats allow researchers to highlight contributions beyond their publication list.Credit: Getty

In December 2021, UK Research and Innovation (UKRI), the largest public funder of UK science, announced that it was abandoning the use of the conventional CV — curriculum vitae — in funding applications. The funding body said it would adopt a new type of CV to "enable people to better demonstrate their contributions to research, teams, and wider society".

As institutions and funders around the world reassess their approach to researcher evaluations, there's a growing call to revamp the academic CVs used to support applications for jobs, funding, promotions and awards. Researchers need to find fresh ways to document their accomplishments and value beyond a mere listing of publications, and committees overseeing promotions and grants need to change their protocols and expectations, says Needhi Bhalla, a cell biologist at the University of California, Santa Cruz. "CVs should reflect the authentic experience of being a scientist," she says, including mentorship, work on committees, outreach and many other contributions that don't result in publications. "I'm excited that we're in the process of rethinking them."

CVs have long been part of the currency of scientific promotion. Scientists seeking a position or a grant often feel obliged to list every publication, presentation and award in a single document intended to sway committees through its sheer length and volume. The typical CV follows a time-worn template, says Robert Morrell, an education researcher and former director of the New Generation of Academics Programme at the University of Cape Town in South Africa. " 'I was born, I went to school here, I had these publications, these are the students I graduated.' People who write CVs like that are missing the boat."

The UKRI is not alone in seeking to rethink the CV in response to a renewed focus on team science and equity, diversity and inclusion (EDI). It modelled its new CV format on 'Résumé for Researchers', introduced in 2019 by the Royal Society in London. Similar initiatives have been unveiled by research councils in the Netherlands and Luxembourg.

In response, researchers are learning how to rework CVs to emphasize quality over quantity, and to include narratives about their broader impact. Meanwhile, hiring panels and grant evaluators need to rethink how best to assess these documents.

The core problem with standard CVs is that they tend to reduce scientists to numbers, says Rebecca Pillai Riddell, a behavioural scientist and associate vice-president of research at York University in Toronto, Canada. Evaluating researchers on the basis of sheer number of publications or using related measures, such as the impact factors of the journals in which they publish, ignores many things that go into a scientific career, Pillai Riddell says. Conventional CVs "are supposed to be quick-and-dirty summaries", she says. As someone who has seen many over the years, she knows that those summaries can contain valuable information, even if the emphasis is often misplaced. "They focus on counting, not on what's important."

The 'quantity above quality' approach is especially short-sighted and unfair in the wake of the COVID-19 pandemic, Pillai Riddell says. Many researchers simply didn't have the time or opportunity to conduct experiments or crank out papers at their normal pace during shutdowns. And as schools closed their doors, many scientists who were also parents had to shift their priorities from work to home, especially women. "If we continue to emphasize quantity, caregivers are not going to be eligible for grants or awards," she adds.

Scientists and institutions alike need to reconsider the entire purpose of a CV, says Wolfgang Kaltenbrunner, a sociologist of science at Leiden University in the Netherlands. "To make science work, you need to accomplish a lot of tasks that are not easily represented in a CV," he says, such as communicating science to the general public and collaborating behind the scenes on big projects. "Are we selecting for the right things in grant funding or tenure? There's widespread discontent with it in science."

Robert Morrell (in purple top) on a retreat with early-career researchers in South Africa.Credit: Robert Morrell

Contributions that count

Kaltenbrunner co-authored a 2021 commentary in *Humanities & Social Science Communications* that offered ten suggestions for revamping academic CVs to make them a fairer gauge of scientific talent[1]. They include a new focus on "activities and outputs that are relevant". That means moving away from exhaustive lists of publications and presentations, and cutting down on 'noise' that doesn't reflect qualifications for a job or grant. Instead of including everything that has ever carried their name, researchers should list a few meaningful publications that hiring managers and evaluators could realistically take the time to read and appreciate, Kaltenbrunner and his colleagues say. "Focusing on only a few outputs saves researcher and evaluator resources, discourages salami slicing of results, improves comparison between early- and late-career researchers and renders publication hiatuses as a result of career breaks less apparent," they write. Importantly, such an approach would help to level the playing field when early-career and senior scholars are directly competing.

Pillai Riddell would welcome a résumé revolution that cuts down on reading for those who assess applicants. "I'm thinking about reviewer burdens," she says. "In my dream scenario, you'd pick two papers and provide a 200-word summary of the importance of the paper. It allows for contextualization."

Kaltenbrunner notes that many academic jobs require a covering letter, which gives applicants another opportunity to tell the story of their careers and highlight their most important papers. "They can use the narrative to fill gaps that are left by the publication record," he says.

Publication lists aren't as meaningful today as they might have been for previous generations of scientists, Kaltenbrunner says. "Science has become increasingly competitive in the past 40 years, so the publication lists have become much longer," he says. "It's not necessarily true that people have more ideas, but publication conventions have changed. Competition actually reduced the informational value of CVs."

Appraising someone according to their number of publications and how many times these have been cited also greatly favours researchers in particular fields, Pillai Riddell says. "If you're studying bird mating calls instead of cancer, you aren't going to have the same number of hits," she says. She adds that medical researchers can show up on 20–30 papers a year, an impossible standard for someone in a field such as behavioural science. Such comparisons can become important in the context of international awards that attract applicants from across the scientific spectrum. Grant-awarding bodies should embrace diversity of scientific fields as well as other forms of diversity, she says.

CVs could be more effective if they allowed room for narratives — brief statements that tell a story about a scientist, their accomplishments or their impact. "A narrative section would give them room to explain their achievements and contributions to science that do not fit traditional CV categories," Kaltenbrunner says. With a narrative section, "they could tell stories of successful engagement with a stakeholder, contributions in terms of community service, or excellence in teaching or supervision". (See 'CV snapshots' for examples.)

CV snapshots

These excerpts are from the narrative CVs of successful applicants to the Luxembourg National Research Fund in 2021.

• "Alongside scientific goals, I also follow leadership ones. A four-day professional leadership course and three months of personal coaching in 2020 taught me to reflect on myself, develop my scientific vision and learn about key attributes of successful teams. I also sent my postdocs on similar courses. As a result, my team is extremely productive, with two manuscripts at the submission stage only 2.5 years after the launch of my own group."

• "I give regular talks at foundations, charity clubs and student associations, telling young people about scientific research and new therapeutic avenues in cancer. I also regularly write for national newspapers, again to transfer my passion for research to younger people."

• "I invest in the development of individuals and build up a strong team spirit by regularly taking leadership and conflict-management courses. During the COVID-19 pandemic, I put into practice various ideas on remote leadership and team communication."

• "I made a 52-minute documentary about contemporary psychiatry in my country, together with a visual anthropologist and a local production company. We worked as care assistants on a ward for three months before introducing a camera. The film proved to be a stimulating exercise in public engagement."

The term 'narrative CV' is gaining traction, but Kaltenbrunner says he's not actually a fan of that label. "It's binary," he says. "It suggests that a CV is either narrative or not narrative." He prefers 'contextual CV': "It's more about supplementing traditional CVs with other elements." He notes that the use of alternative CV formats by research councils in the Netherlands and Luxembourg has dismayed some, more senior, researchers. "Some see these experimental CV formats as an undue intervention by funders," Kaltenbrunner says. "They have made a career based on existing criteria."

The Luxembourg National Research Fund says the narrative CV model, introduced last year, will "allow an applicant to be more fairly evaluated on their scientific vision, appropriate experience, and contributions to science and society". Similarly, the Royal Society's Résumé for Researchers is a narrative-based document that is focused on four key questions: how have you contributed to the generation of knowledge? How have you contributed to the development of individuals? How have you contributed to the wider research community? And how have you contributed to broader society?

Documenting diverse work

A new era of CVs could help to promote diversity in science, Bhalla says. "Traditional metrics of what you've published, where you've published and who you've published with, are definite barriers to diversity, equity and inclusion," she says. Scientists who might not have wowed evaluators in the past with their publications and impact factors would have a chance to explain their mentorship, outreach and committee duties — areas where women and people from minority ethnic groups and other under-represented demographics often excel (see 'Building a standout CV').

Building a standout CV

When he was director of the New Generation of Academics Programme, a South African initiative to recruit a diverse cohort of promising scholars to academia, Robert Morrell worked to give young researchers an edge. In many cases, that meant helping them to build a CV that truly captured their skills and potential, says Morrell, who retired from the position in 2021. "My job was to help people get promoted."

He encourages researchers to "harvest evidence" of their work and its impact. It's especially important to keep track of things that can't be measured easily, including positive feedback from students or collaborators.

"I urge people to keep [complimentary] e-mails and file them in a separate folder," he says, such as messages of praise for participating in a big team project. "Those types of examples are really helpful, and people don't think of [including] them. They think it's immodest."

Likewise, Rebecca Pillai Riddell, associate vice-president of research at York University in Toronto, Canada, always keeps meticulous track of time and effort spent on mentoring, teaching and serving on committees. "Nobody is going to track it for me," she says. "To survive in academia, to get leadership roles, you have to advocate for yourself."

Pillai Riddell says it's easier to build a case for yourself if you organize your work systematically. "You need to create structures," she says. For example, as an advocate for under-represented students, she has set aside 2 hours of office time every week specifically for them. She doesn't keep track of everything that's discussed, but she can report how many students have dropped in. "It's about getting credit for what you're already doing."

Equity statements have become an increasingly common requirement for CVs, and universities that require such statements have experienced greater diversity in subsequent recruitment[2]. Riddell recommends including such a statement even if it's not required. "You can say, 'My commitment to equity requires that I tell you about this.'"

In a 2019 article in *Molecular Biology of the Cell*, Bhalla laid out a series of strategies to improve equity in faculty hiring[2]. Among other things, she suggested augmenting conventional CVs with short statements that summarize an applicant's research contributions during their graduate studies and as postdocs.

Bhalla says that there's been some pushback in the science community against any sort of narrative sections on CVs. Some say that asking scientists to explain the impact or importance of their work provides an unfair advantage for people with strong communication skills while hindering people who might not be as persuasive, including scientists who speak English as a second or third language. But Bhalla says being able to explain one's research is a fundamental part of being a scientist. "Those are skill sets that you're going to need anyway if you're writing a grant," she says. "So that's one of the skills that we should be assessing."

Such messages, no matter how well crafted, will only work if evaluators are ready to accept them, Riddell says. She's encouraged by the growing number of institutions that have signed the San Francisco Declaration on Research Assessment, a framework that, among other things, discourages the use of impact factors in hiring and funding decisions.

In March, Pillai Riddell and her team at York University launched POLARIS, an online training course to help members of the university's hiring and funding committees to update how they evaluate researchers. One of the course's main goals is to encourage participants to look beyond CVs to consider EDI issues in their decisions. It includes modules in which participants rank hypothetical candidates and discuss their choices with the EDI programme manager. The training also includes videos of experienced evaluators discussing best practice. Pillai Riddell says that some of the videos captured real-life arguments, signifying the tension and passion that goes into researcher evaluation. After completing the course, participants receive a certificate that, naturally, can be included on their CV. (A version of the course is available to external researchers as well.)

The current use of CVs also hinders the career progression of scientists in developing countries who must get by with limited resources and infrastructure, says Olumuyiwa Asaolu, an engineer at the University of Lagos in Nigeria. In a 2020 opinion piece for the academic news site The Conversation, Asaolu called for a fresh approach to evaluating African researchers, including rethinking the CV. The emphasis on publications and impact factors is especially problematic, he says, partly because of costly publication fees. "It's not easy for Africans to publish in the big journals."

Asaolu, who completed a postdoctoral position at the University of Tennessee at Knoxville in the early 2000s, says that publishing while working in different countries has given him insight into disparities. "The response you get if your address is in Africa is not the same as the response or treatment you get if you're sending your manuscript from a Western institution."

In 2018, a web-based survey of 267 African researchers conducted by Asaolu and his colleagues underscored doubts about standard metrics[3]. Although the majority (59%) of respondents agreed that impact factor is a true measure of a journal's quality, only 40% agreed that publishing in journals with high impact factors should remain a major component of winning grants and promotions.

An approach to CVs that focuses more on real-world contributions — including projects that help local communities — and less on impact factors could help to level the playing field for African researchers who are applying for positions or grants overseas, Asaolu says. But he adds that young researchers can't take it on themselves to reinvent the system. As a mentor, he often assists others with their applications, and encourages them to follow existing instructions and templates as closely as possible. "Change has to be incremental," he says.

Incremental or not, changes to the format of CVs are inevitable, Pillai Riddell says. Early-career researchers can do their part by expanding their own definitions of what's worth listing and, more fundamentally, what it means to be a successful scientist. They can certainly mention a paper of theirs with thousands of downloads, but shouldn't ignore the impact they've had on their communities: "Both have a place."

Nature **604**, 203-205 (2022), *doi: https://doi.org/10.1038/d41586-022-00928-4*

References

1. Strinzel, M., Brown, J., Kaltenbrunner, W., de Rijcke, S. & Hill, M. *Humanit. Soc. Sci. Commun.* **8**, 251 (2021). Article Google Scholar

2. Bhalla, N. *Mol. Biol. Cell* **30**, 2744–2749 (2019). PubMed Article Google Scholar

3. Atolani, O. *et al.* in *Globafricalisation and Sustainable Development* https://doi.org/10.2478/9783110671049-010 (Sciendo, 2019). Google Scholar

(Nature, 05 April 2022, https://www.nature.com/articles/d41586-022-00928-4)

ΝΕΑ ΑΠΟ ΤΙΣ ΕΛΛΗΝΙΚΕΣ ΚΑΙ ΔΙΕΘΝΕΙΣ ΓΕΩΤΕΧΝΙΚΕΣ ΕΝΩΣΕΙΣ

Εκπαιδευτική εκδρομή του Τομέα Γεωτεχνικής της Σχολής Πολιτικών Μηχανικών του Ε.Μ.Π. σε τεχνικά έργα στην Ιταλία, Γαλλία και Ελλάδα (14-23 Απριλίου 2022) με έμφαση σε περιστατικά κλασικών αστοχιών

Η εκδρομή αυτή αποτελεί ένα ιδιαίτερα σημαντικό συμπλήρωμα του εκπαιδευτικού κύκλου της διδασκαλίας των Πολιτικών Μηχανικών του ΕΜΠ, προσφέροντας πραγματικές παραστάσεις στο φοιτητή, διευκολύνοντας στην αφομοίωση των απαραίτητων γνώσεων που του παρέχονται «από έδρας». Κύριο χαρακτηριστικό της εκδρομής αυτής είναι η επίσκεψη ιδιαιτέρως μεγάλων και γνωστών σε παγκόσμια κλίμακα περιστατικών αστοχιών, ή ακόμα και τραγικών καταστροφών, που συνέβησαν λόγω κυρίως γεωλογικών ατελειών που είτε δεν αναγνωρίσθηκαν κατά τη μελέτη είτε που ο ρόλος τους υποεκτιμήθηκε. Οι εμπειρίες που αποκτήθηκαν από τα τραγικά αυτά συμβάντα συνέβαλαν, από την άλλη πλευρά, στην εξέλιξη των εφαρμογών της Γεωλογίας στα έργα Μηχανικού και στη συνεχώς πιο αξιόπιστη κατασκευή των έργων.

Προπτυχιακοί φοιτητές 4ου έτους εκπαιδεύτηκαν μπροστά στις φυσικές κλίμακες των έργων τους, στο πλαίσιο του μαθήματος "Τεχνική γεωλογία", σε μια 10ήμερη εκδρομή στην Ιταλία και Γαλλία με τεχνικές επισκέψεις σε:

- Μεγάλες αλλά και τραγικές αστοχίες έργων Πολιτικού Μηχανικού
- Πολύ μεγάλες -κλίμακας πλαγιάς και βουνού- κατολισθήσεις
- Θέματα γεωτεχνικής παρακολούθησης, διαχείρισης και λήψης αποφάσεων έναντι εκδήλωσης γεωκινδύνων
- Μεγάλες και βαθιές σήραγγες(οδικές και σιδηροδρομικές) των Άλπεων
- Έργα αντιστηρίξεων βραχωδών πρανών σε αυτοκινητοδρόμους και σε περιβάλλον ορεινής οδοποιίας
- Θέματα θεμελιώσεων ιστορικών μνημείων και λήψης μέτρων προστασίας
- Τεχνικά Έργα σε σεισμικά ενεργό περιβάλλον

Υπεύθυνος και συνοδός της εκπαιδευτικής εκδρομής ήταν ο Επίκουρος Καθηγητής του Τομέα Γεωτεχνικής της Σχολής Πολιτικών Μηχανικών, Βασίλης Μαρίνος (marinosv@civil.ntua.gr).

Σχετικές αναρτήσεις της εκπαιδευτικής εκδρομής σε μέσα κοινωνικής δικτύωσης του Εθνικού Μετσόβιου Πολυτεχνείου, της Σχολής Πολιτικών Μηχανικών και του Τομέα Γεωτεχνικής μπορείτε να βρείτε εδώ:

1. https://www.linkedin.com/posts/national-technical-university-of-athens_excursion-tour-mountain-activity-6927523830684889088-8JSG?utm_source=linkedin_share&utm_medium=member_desktop_web
2. https://www.linkedin.com/feed/update/urn:li:activity:6920226704816803840/
3. https://www.ntua.gr/el/news/announcements/item/2655-i-emvlimatiki-ekpaideftiki-ekdromi-tis-sxolis-politikon-mixanikon-tou-emp-anavionei
4. http://www.civil.ntua.gr/news/2022/4/12/ekdromi/
5. http://www.civil.ntua.gr/news/2022/5/5/ekdromi/
6. https://www.facebook.com/permalink.php?story_fbid=366025622214173&id=100261155457289
7. https://www.facebook.com/permalink.php?story_fbid=366025622214173&id=100261155457289

Η επιτυχία αυτής της εκδρομής ήταν αποτέλεσμα της συνεχούς και στενής συνεργασίας του Επίκουρου Καθηγητή του Γεωτεχνικού Τομέα της Σχολής Πολιτικών Μηχανικών του ΕΜΠ Βασίλη Μαρίνου, της επιτροπής των φοιτητών του έτους αλλά και όλων των 78 φοιτητών! Η συνέργεια ήταν υποδειγματική.

Το χαμόγελο δεν έφυγε ποτέ από τα πρόσωπα των φοιτητών, παρά το δύσκολο πρόγραμμα μας!

Όλες οι εικόνες που απαθανάτισαν, οι πραγματικές κλίμακες, οι τεχνικές πληροφορίες κάθε αντικειμένου που αναλύθηκαν, κάθε αίσθηση που απέκτησαν μέσα σε αυτές τις 10 ημέρες, θα τους συνοδεύουν στη ζωή τους. Ένα βιβλίο 800 σελίδων, ειδικά προετοιμασμένο για αυτήν την εκδρομή, θα εμπλουτίσει την προσωπική τους βιβλιοθήκη.

Η εκδρομή αυτή αποτελεί συνέχεια της ιστορικής εκδρομής (η 1η εκδρομή πραγματοποιήθηκε το 1992) του 6ου εξαμήνου Πολιτικών Μηχανικών του Ε.Μ.Π., η οποία οφείλει το ξεκίνημα και την εδραίωση της στον αείμνηστο Ομότιμο καθηγητή Παύλο Μαρίνο και τον Ομότιμο καθηγητή Γεώργιο Τσιαμπάο, καθώς και σε πλήθος άλλων συνεργατών από τον τομέα Γεωτεχνικής Μηχανικής.

Δρ. Βασίλης Μαρίνος

Ελληνικός Σύνδεσμος Γεωσυνθετικών Υλικών
www.igs-greece.gr

Γενική Συνέλευση - Εκλογές

Στις 8 Απριλίου 2022, πραγματοποιήθηκε με επιτυχία η εξ αναβολής τακτική εκλογική Γενική Συνέλευση του Ελληνικού Συνδέσμου Γεωσυνθετικών Υλικών, μέσω τηλεδιάσκεψης, κατόπιν σχετικής πρόσκλησης που στάλθηκε στα μέλη του ΕΣΓΥ.

Συζητήθηκαν τα παρακάτω θέματα:

- Εγγραφές νέων μελών
- Πεπραγμένα - Οικονομικός Απολογισμός
- Δραστηριότητες Ελληνικού και Διεθνών Συνδέσμων Γεωσυνθετικών Υλικών
- Εκλογή νέου Διοικητικού Συμβουλίου για την περίοδο 2022-2025.
- Εκλογή Εξελεγκτικής Επιτροπής για την περίοδο 2022-2025.

Κατόπιν ηλεκτρονικής ψηφοφορίας, επί συνόλου 15 ψηφισάντων, εκλέχθηκαν για την επόμενη περίοδο - τριετία 2019 – 2022, οι κάτωθι:

(1) Διοικητικό Συμβούλιο Δ.Σ.:

Απόστολος Ρίτσος (15 ψήφοι) - Χρήστος Στρατάκος (15 ψήφοι) – Νικόλαος Τσάτσος (14 ψήφοι) - Ιωάννης Μάρκου (12 ψήφοι) - Ιωάννης Ψιμής (12 ψήφοι) - Ιωάννης Φίκιρης (11 ψήφοι) – Κωνσταντίνος Σαμαράς (10 ψήφοι)

(2) Εξελεγκτική Επιτροπή:

Ιωάννης Ζευγώλης (9 ψήφοι) - Αλέξανδρος Τσιτόπουλος (7 ψήφοι) – Ιωάννης Γουρδουμπάς (3 ψήφοι) - Κωνσταντίνος Μπαντραλέξης (3 ψήφοι)

Ο κος Ιωάννης Ζευγώλης δήλωσε ότι παραχωρεί τη θέση του στην Ε.Ε.

Την 28η Απριλίου 2022 τα εκλεγμένα μέλη της ψηφοφορίας της Γενικής Συνέλευσης της 8ης Απριλίου 2022 (βλέπε σχετικά και το πρακτικό της εφορευτικής επιτροπής της 8ης Απριλίου 2022) συγκροτήθηκαν σε σώμα με την ακόλουθη σύνθεση:

Πρόεδρος: Μάρκου Ιωάννης
Αναπληρωτής Πρόεδρος: Ρίτσος Απόστολος
Υπεύθυνος Οικονομικών: Τσάτσος Νικόλαος
Γραμματέας: Στρατάκος Χρήστος
Μέλος: Ψιμής Ιωάννης
Μέλος: Φίκιρης Ιωάννης
Μέλος: Σαμαράς Κωνσταντίνος

Εκ μέρους του Δ.Σ. του Συνδέσμου,

Χρήστος Στρατάκος - Γραμματέας HGS

International Society for Soil Mechanics and Geotechnical Engineering

South African Geotechnical Division Time Capsule goes live

The South African Geotechnical Division is directly affiliated with the South African Institution of Civil Engineering (SAICE) and its main objective is to provide members with the latest developments in Geotechnical Engineering practice in South Africa. The committee, comprising practising geotechnical engineers from the consulting, contracting and academic spheres has developed a comprehensive blog for the ISSMGE Time Capsule, outlining some of the key developments of geotechnical engineering in South Africa since the fields inception.

The South African Geotechnical Engineering Time Capsule Blog highlights key academic, technical, and historical achievements and projects over the years, noting the contributions of luminaries such as Professor Jere Jennings and Dr Tony Brink among others.

This project is an opportunity to record past, present and future achievements, and issues in Geotechnical Engineering practice in South Africa. This will provide a perpetual database of information which can encourage and inspire students and individuals to join our Geotechnical Community, and for current members to interact around.

It is expected to become an ongoing project to which the Geotechnical Division members are encouraged to contribute articles on the major construction or project developments they or other key individuals have been involved in, their areas of contribution, key outcomes and ongoing applications of relevant technologies, new avenues to explore, etc., while highlighting the development of geotechnical engineering as a discipline and the experience of the contributor.

About the authors:

John Pavlakis is a Geotechnical Engineer practicing at Michael Pavlakis and Associates and the Chairman of the South African Institution of Civil Engineers Geotechnical Division. John has been working in the geotechnical field for the last 15 years and has a keen interest in assessment of risks as-sociated with the developments on Dolomite land and the use of the Menard Pressuremeter. His hobbies include travelling, reading, cycling and most importantly spending time with family and friends.

Jacobus Breyl has been part of the Geotechnical Department at Jones & Wagener for 14 years. After being involved in geotechnical design and site investigations in the initial years, he has been involved in assessing the surface stability of undermined ground in recent years.

About these articles:

To debate past, current and future issues in Geotechnical Engineering, the Time Capsule Project is welcoming and publishing short articles on the ISSMGE website.

We challenge you to write 200-400 words on any topic that will generate debate within the Geotechnical Engineering profession. Click here to submit your message for consideration.

Articles will be displayed for a limited time and views expressed need not be shared by the ISSMGE or held strongly by authors.

Charles MacRobert / Time Capsule Project / 01-04-2022

4th International Conference on Information Technology in Geo-Engineering (04 - 05 Aug 2022)

Invitation for Papers:

The 4th ICITG aims to address the latest developments in applications of information technologies and artificial intelligence to geo-engineering. Topics of the conference cover any topics related to the applications of information technologies in geotechnical engineering, geo-environmental engineering, or engineering geology. These include, but not limited to, the following topics:

- Sensors and sensing technologies for geotechnical or geological applications
- New geotechnical instrumentations, data collection and transmission technologies
- 3D geological modeling
- Application of Artificial intelligence (AI) or machine learning in geotechnical engineering
- Use of Information and Communications Technologies (ICT) in laboratory and field works
- Digitalisation for site investigation, in-situ or laboratory testing
- Data driven geophysical investigation and interpretation methods
- Big data and database processing for better use of geotechnical data for geotechnical design
- Applications of imaging technologies for geotechnical design or geological data presentations
- Building Information Modeling (BIM) applied to geo-structures and underground constructions
- Virtual reality and augmented reality
- Intelligent geomaterials, geosynthetics and geosystems
- Case studies in design, constructions and maintenance

For the conference, only extended abstract needs to be submitted for the consideration for oral presentation. Selected papers will be invited for submissions to special issues in Acta Geotechnica and Georisk.

Important Dates:

- Abstract for Conference / Special Journal Issues 15 May 2022

- Confirmation of Acceptance of Abstract 31 May 2022

About ICITG:

The International Conference on Information Technology in Geo-Engineering (ICITG) was initiated by the Joint Technical Committee 2 (JTC2) of the Federation of International Geo-Engineering Societies (FedIGS).

FedIGS is an umbrella organization linking international professional societies in the field of "GeoEngineering", including ISSMGE (International Society for Soil Mechanics and Geotechnical Engineering), ISRM (International Society for Rock Mechanics and Rock Engineering), IAEG (International Association for Engineering Geology and the Environment), IGS (International Geosynthetics Society). JTC2 is one committee under FedIGS and focuses on intelligentizing geo-engineering data.

The conference intends to bring together engineers, scientists, researchers and educators to review new developments and IT advances in geo-engineering and provide a forum for the discussion of future trends. The first three ICITG conferences were organized by Tongji University, Shanghai, China in 2010, Durham University, Durham, UK together with Tongji University, Shanghai, China in 2014, and the University of Minho and the Portuguese Geotechnical Society in Portugal in 2019, respectively. The 4th ICITG will be organized by the Geotechnical Society of Singapore, with the support of Nanyang Technological University and National University of Singapore.

More information on the conference can be found in the conference website: https://www.4iticg.org/

Conference Chairs:

CHU Jian, Nanyang Technological University
LEUNG Chun Fai, National University of Singapore

Siau Chen Chian / TC217 / 07-04-2022

Rocscience - Course: 2D & 3D Slope Stability Analysis

rocscience

Description:

On popular demand, we are bringing the in-person course on 2D and 3D Slope Stability Analysis to our users in Europe! Join us in Madrid, Spain for the course on May 30-31, 2022. Seats are limited.

link for the registration:

https://www.rocscience.com/events/course-2d-3d-slope-stability-analysis-madrid2022

Data/Time: May 30-31, 2022
Location: Madrid, Spain

ISSMGE Secretariat / Corporate Associates / 22-04-2022

Geotechnical Engineering Education "Time Capsule" Report

The contribution of TC306 to the Time Capsule Project has been uploaded under the tab "Reports" of the TC306 webpage. The contents of the TC306 Time Capsule Report were discussed at the committee meeting of April 2021 and the country-specific contributions were provided by TC306 members. Being a group effort, the report can be used for introducing TC306, its past, present and possible future.

Marina Pantazidou / TC306 / 28-04-2022

Reference List for Machine Learning and its Applications in Geotechnical Engineering - PART I: NEED TO KNOW KNOWLEDGE

1 Probability Theory

[1] Jeffreys, H. (1983). Theory of Probability. Oxford University Press, Oxford, New York.

[2] Sivia, D.S., and Skilling, J. (2006). Data Analysis: A Bayesian Tutorial. Oxford University Press, New York.

[3] Ang, A.H.-S., and Tang, W.H. (2007). Probability concepts in engineering, Vol. I Emphasis on applications to civil and environmental engineering, 2nd Ed. Wiley, New York.

[4] Beck, J.L. (2010). Bayesian system identification based on probability logic. Structural Control and Health Monitoring, 17(7), 825847.

[5] Yuen, K.V. (2010). Bayesian Methods for Structural Dynamics and Civil Engineering. John Wiley & Sons, ISBN: 978-0-470-82454-2.

[6] Gelman, A., et al. (2013). Bayesian Data Analysis, Third Edition. Chapman and Hall/CRC.

2 Information Theory

[7] Cover, T. M. and J. A. Thomas (1991). Elements of Information Theory. Wiley.

[8] MacKay, D. J. C. (2003). Information Theory, Inference and Learning Algorithms. Cambridge University Press.

3 Decision Theory

[9] Berger, J. O. (1985). Statistical Decision Theory and Bayesian Analysis (Second ed.). Springer.

[10] Bather, J. (2000). Decision Theory: An Introduction to Dynamic Programming and Sequential Decisions. Wiley.

4 Introductory Materials on Machine Learning

[11] Mitchell, T. (1997). Machine Learning. McGraw Hill.

[12] Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer-Verlag New York.

[13] Barber, D. (2012). Bayesian Reasoning and Machine Learning. Cambridge University Press.

[14] Farrar, C. R., and Worden, K. (2012). Structural health monitoring: a machine learning perspective. John Wiley and Sons.

[15] Alpaydin, E. (2014). Introduction to Machine Learning, Third Edition. The MIT Press, London.

Dongming Zhang / TC309 / 29-04-2022

Reference List for Machine Learning and its Applications in Geotechnical Engineering - PART II: MACHINE LEARNING ALGORITHMS

1 Supervised learning

1.1 Decision tree learning

[1] Breiman, Leo, Friedman, J. H., Olshen, R. A. and Stone, C. J. (1984). Classification and regression trees. Monterey, CA: Wadsworth and Brooks/Cole Advanced Books and Software. (Google citation: 37373)

[2] Dattatreya, G. R., and Kanal, L. N. (1985). Decision trees in pattern recognition. University of Maryland. Computer Science.

[3] Safavian, S. R., and Landgrebe, D. (1991). A survey of decision tree classifier methodology. IEEE Transactions on Systems, Man Cybern., 21(3), 660-674.

[4] Murthy, S. K., Kasif, S., and Salzberg, S. (1994). A system for induction of oblique decision trees. Journal of Artificial Intelligence Research, 2, 1-32.

[5] Friedl, M. A., and Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. Remote Sensing of Environment, 61(3), 399-409.

[6] Murthy, S. K. (1998). Automatic construction of decision trees from data: A multi-disciplinary survey. Data Mining and Knowledge Discovery, 2(4), 345-389.

[7] Kohavi, R., and Quinlan, J. R. (2002). Data mining tasks and methods: Classification: decision-tree discovery. In Handbook of data mining and knowledge discovery (pp. 267-276). Oxford University Press, Inc.

[8] Rokach, L.; Maimon, O. (2005). Top-down induction of decision trees classifiers-a survey. IEEE Transactions on Systems, Man, and Cybernetics, Part C. 35 (4): 476487.

[9] Barros, Rodrigo C., Basgalupp, M. P., Carvalho, A. C. P. L. F., Freitas, Alex A. (2012). A Survey of Evolutionary Algorithms for Decision-Tree Induction. IEEE Transactions on Systems, Man and Cybernetics, Part C: Applications and Reviews, 42(3), 291-312.

[10] James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). An Introduction to Statistical Learning (Vol. 112). New York: springer. (Google citation: 2673)

[11] Lior, R. (2014). Data mining with decision trees: theory and applications (Vol. 81). World scientific.

1.2 Artificial neural networks

[12] McCulloch, W. S., and Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. The Bulletin of Mathematical Biophysics, 5(4), 115-133. (Google citation: 15445)

[13] White, H. (1989). Learning in artificial neural networks: A statistical perspective. Neural Computation, 1(4), 425-464.

[14] Maren, A., Harston, C., and Pap, R. (1990). Handbook of neural computing applications. Academic Press, Inc., San Diego, California

[15] Ghaboussi, J., Garrett, J. H., and Wu, X. (1991). Knowledge based modeling of material behaviour with neural networks. Journal of Engineering Mechanics, ASCE, 117(1), 132153.

[16] Hunt, K. J., Sbarbaro, D., bikowski, R., and Gawthrop, P. J. (1992). Neural networks for control systemsa survey. Automatica, 28(6), 1083-1112.

[17] Zurada, J. M. (1992). Introduction to artificial neural systems. West Publishing Company, St. Paul.

[18] Yao, X. (1993). A review of evolutionary artificial neural networks. International Journal of Intelligent Systems, 8(4), 539-567.

[19] Garrett, J. H. (1994). Where and why artificial neural networks are applicable in civil engineering. Journal of Computing in Civil Engineering, ASCE, 8(2), 129130.

[20] Fausett, L. V. (1994). Fundamentals neural networks: Architecture, algorithms, and applications. Prentice-Hall, Inc., Englewood Cliffs, New Jersey.

[21] Bishop, C. M. (1995). Neural networks for pattern recognition. Oxford University Press.

[22] Ripley, B. D. (1996). Pattern recognition and neural networks. Cambridge University Press. (Google citation: 7483)

[23] Yao, X., and Liu, Y. (1997). A new evolutionary system for evolving artificial neural networks. IEEE Transactions on Neural Networks, 8(3), 694-713.

[24] Schalkoff, R. J. (1997). Artificial neural networks (Vol. 1). New York: McGraw-Hill.

[25] Gardner, M. W., and Dorling, S. R. (1998). Artificial neural networks (the multilayer perceptron)a review of applications in the atmospheric sciences. Atmospheric Environment, 32(14), 2627-2636.

[26] Zhang, G., Patuwo, B. E., and Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. International Journal of Forecasting, 14(1), 35-62.

[27] Zhang, G. P. (2000). Neural networks for classification: a survey. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 30(4), 451-462.

[28] Shahin, M. A., Maier, H. R. and Jaksa, M. B. (2005). Investigation into the Robustness of Artificial Neural Network Models for a Case Study in Civil Engineering. In MODSIM 2005 International Congress on Modelling and Simulation, Zerger, A. and Argent, R.M. (eds), Modelling and Simulation Society of Australia and New Zealand, Melbourne, December 1215, pp. 7983. ISBN: 0-9758400-2-9.

[29] Hinton, G. E., and Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. Science, 313(5786), 504-507.

1.3 Deep learning

[30] Dechter, R. (1986). Learning while searching in constraint-satisfaction problems. University of California, Computer Science Department, Cognitive Systems Laboratory.

[31] Ngiam, J., Khosla, A., Kim, M., Nam, J., Lee, H., and Ng, A. Y. (2011). Multimodal deep learning. In Proceedings of the 28th International Conference on Machine Learning (ICML-11) (pp. 689-696).

[32] Deng, L., and Yu, D. (2014). Deep Learning: Methods and Applications. Foundations and Trends in Signal Processing, 7 (34), 1199.

[33] Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural Networks, 61, 85-117.

[34] LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep Learning. Nature, 521, 436-444. (Google citation: 6899)

1.4 Inductive logic programming

[35] Muggleton, S. H. (1991). Inductive logic programming. New Generation Computing. 8 (4): 295318.

[36] Muggleton, S., and De Raedt, L. (1994). Inductive Logic Programming: Theory and methods. The Journal of Logic Programming, 1920, 629679. (Google citation: 1708)

[37] Lavrac, N., and Dzeroski, S. (1994). Inductive Logic Programming: Techniques and Applications. New York: Ellis Horwood.

[38] De Raedt, L. (1999). A perspective on inductive logic programming. In the Logic Programming Paradigm (pp. 335-346). Springer, Berlin, Heidelberg.

[39] Muggleton, S. (1999). Inductive logic programming: issues, results and the challenge of learning language in logic. Artificial Intelligence, 114(1-2), 283-296.

1.5 Support vector machines

[40] Cortes, C., and Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273297.

[41] Cristianini, N., and Shawe-Taylor, J. (2000). An introduction to support vector machines and other kernel-based learning methods. Cambridge university press.

[42] Ben-Hur, A., Horn, D., Siegelmann, H. T., and Vapnik, V. (2001). Support vector clustering. Journal of Machine Learning Research, 2(Dec), 125-137.

[43] William H., Teukolsky, Saul A., Vetterling, William T., and Flannery, B. P. (2007). Numerical Recipes: The Art of Scientific Computing (3rd ed.). New York: Cambridge University Press. (Google citation: 116107)

[44] Steinwart, I., and Christmann, A. (2008). Support Vector Machines. Springer-Verlag, New York.

[45] Chang, C. C., and Lin, C. J. (2011). LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology. 2 (3). (Google citation: 36612)

1.6 Similarity and metric learning

[46] Davis, J. V., Kulis, B., Jain, P., Sra, S., and Dhillon, I. S. (2007). Information-theoretic metric learning. International Conference in Machine Learning (ICML): 209216. (Google citation: 1580)

[47] Kulis, B. (2013). Metric learning: A survey. Foundations and Trends in Machine Learning, 5(4), 287-364.

[48] Bellet, A., Habrard, A., and Sebban, M. (2013). A survey on metric learning for feature vectors and structured data. arXiv preprint arXiv:1306.6709.

1.7 Sparse dictionary learning

[49] Engan, K.; Aase, S. O.; Hakon Husoy, J. (1999). Method of optimal directions for frame design. IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings. 5, 4432446.

[50] Kreutz-Delgado, K., Murray, J. F., Rao, B. D., Engan, K., Lee, T. W., and Sejnowski, T. J. (2003). Dictionary learning algorithms for sparse representation. Neural Computation, 15(2), 349-396. (Google citation: 714)

[51] Aharon, M., Elad, M., and Bruckstein, A. (2006). rmK-SVD: An algorithm for designing overcomplete dictionaries for sparse representation. IEEE Transactions on Signal Processing, 54(11), 4311-4322. (Google citation: 6842)

[52] Elad, M., and Aharon, M. (2006). Image denoising via sparse and redundant representations over learned dictionaries. IEEE Transactions on Image processing, 15(12), 3736-3745.

[53] Mairal, J., Ponce, J., Sapiro, G., Zisserman, A., and Bach, F. R. (2009). Supervised dictionary learning. In Advances in Neural Information Processing Systems (pp. 1033-1040).

[54] Mairal, J., Bach, F., Ponce, J., and Sapiro, G. (2009). Online dictionary learning for sparse coding. In Proceedings of the 26th Annual International Conference on Machine Learning (pp. 689-696). ACM.

[55] Zhang, Q., and Li, B. (2010). Discriminative K-SVD for dictionary learning in face recognition. In Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on (pp. 2691-2698). IEEE.

[56] Tosic, I., and Frossard, P. (2011). Dictionary learning. IEEE Signal Processing Magazine, 28(2), 27-38.

[57] Bengio, Y., Courville, A., and Vincent, P. (2013). Representation learning: A review and new perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(8), 1798-1828.

[58] Zhang, Z., Xu, Y., Yang, J., Li, X., and Zhang, D. (2015). A survey of sparse representation: algorithms and applications. IEEE Digital Object Identifier access, 3, 490-530.

2 Semi-supervised learning

[59] Ratsaby, J., and Venkatesh, S. S. (1995). Learning from a mixture of labeled and unlabeled examples with parametric side information. In Proceedings of The Eighth Annual Conference on Computational Learning Theory (pp. 412-417). ACM.

[60] Chapelle, O., Scholkopf, B., and Zien, A. (2006). Semi-Supervised Learning, MIT Press, Cambridge, MA. (Google citations: 3929)

[61] Belkin, M., Niyogi, P., and Sindhwani, V. (2006). Manifold regularization: A geometric framework for learning from labeled and unlabeled examples. Journal of Machine Learning Research, 7(Nov), 2399-2434.

[62] Zhu, X. (2008). Semi-supervised learning literature survey. Computer Science, University of Wisconsin-Madison, 2(3), 4.

3 Reinforcement learning

[63] Kaelbling, L. P., Littman, M. L., and Moore, A. W. (1996). Reinforcement learning: A survey. Journal of Artificial Intelligence Research, 4, 237-285.

[64] Sutton, R. S., and Barto, A. G. (1998). Reinforcement learning: An introduction. Cambridge: MIT press. (Google Citations: 26015)

[65] Dorigo, M., Birattari, M., and Stutzle, T. (2006). Ant colony optimization. IEEE Computational Intelligence Magazine, 1(4), 28-39.

[66] Wiering, M., and Van Otterlo, M. (2012). Reinforcement Learning. Springer.

[67] Mnih, V., Kavukcuoglu, K., Silver, D., et al. (2015). Human-level control through deep reinforcement learning. Nature, 518(7540), 529.

[68] Sugiyama, M. (2015). Statistical reinforcement learning: modern machine learning approaches. CRC Press.

4 Unsupervised learning

4.1 Clustering

[69] MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In Proceedings of the fifth Berkeley symposium on mathematical statistics and probability 1(14), 281-297.

[70] Dempster, A. P., Laird, N. M., and Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. Journal of The Royal Statistical Society. Series B (methodological), 1-38. (Google Citations: 53387)

[71] Jain, A. K., and Dubes, R. C. (1988). Algorithms for clustering data. Prentice-Hall, Inc.

[72] Zhang, T., Ramakrishnan, R., and Livny, M. (1996). BIRCH: an efficient data clustering method for very large databases. In ACM Sigmod Record, 25(2), 103-114. ACM.

[73] Ester, M., Kriegel, H. P., Sander, J., and Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. In Kdd, 96(34), 226-231.

[74] Ankerst, M., Breunig, M. M., Kriegel, H. P., and Sander, J. (1999). OPTICS: ordering points to identify the clustering structure. In ACM Sigmod record, 28(2), 49-60. ACM.

[75] Jain, A. K., Murty, M. N., and Flynn, P. J. (1999). Data clustering: a review. ACM Computing Surveys (CSUR), 31(3), 264-323.

[76] Ng, A. Y., Jordan, M. I., and Weiss, Y. (2002). On spectral clustering: Analysis and an algorithm. In Advances in Neural Information Processing Systems (pp. 849-856).

[77] Wu, X., Kumar, V., Quinlan, J. R., Ghosh, J., Yang, Q., Motoda, H., ... and Zhou, Z. H. (2008). Top 10 algorithms in data mining. Knowledge and Information Systems, 14(1), 1-37.

[78] McLachlan, G., and Peel, D. (2004). Finite mixture models. John Wiley and Sons.

[79] Jain, A. K. (2010). Data clustering: 50 years beyond K-means. Pattern Recognition Letters, 31(8), 651-666.

[80] Han, J., Pei, J., and Kamber, M. (2011). Data mining: concepts and techniques. Elsevier. (Google Citations: 39607)

[81] Witten, I. H., Frank, E., Hall, M. A., and Pal, C. J. (2016). Data Mining: Practical machine learning tools and techniques. Morgan Kaufmann.

4.2 Feature learning (Dimensionality reduction)

[82] Jolliffe, I. T. (1986). Principal Component Analysis and Factor Analysis. In Principal Component Analysis (pp. 115-128). Springer New York. (Google Citations: 33332)

[83] Kohonen, T. (1998). The self-organizing map. Neurocomputing, 21(1), 1-6. (Google Citations: 23430)

[84] Tenenbaum, J. B., De Silva, V., and Langford, J. C. (2000). A global geometric framework for nonlinear dimensionality reduction. Science, 290(5500), 2319-2323.

[85] Roweis, S. T., and Saul, L. K. (2000). Nonlinear dimensionality reduction by locally linear embedding. Science, 290(5500), 2323-2326.

[86] Hyvärinen, A., Karhunen, J., and Oja, E. (2004). Independent Component Analysis (Vol. 46). John Wiley and Sons.

[87] He, X., and Niyogi, P. (2004). Locality preserving projections. In Advances in Neural Information Processing Systems,(pp. 153-160).

[88] Srebro, N., Rennie, J., and Jaakkola, T. S. (2005). Maximum-margin matrix factorization. In Advances in Neural Information Processing Systems, (pp. 1329-1336).

[89] Hinton, G. E., and Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. Science, 313(5786), 504-507.

4.3 Outlier detection

[90] Knorr, E. M., Ng, R. T., and Tucakov, V. (2000). Distance-based outliers: algorithms and applications. The VLDB JournalThe International Journal on Very Large Data Bases, 8(3-4), 237-253.

[91] Ramaswamy, S., Rastogi, R., and Shim, K. (2000). Efficient algorithms for mining outliers from large data sets. In ACM Sigmod Record, 29(2), 427-438. ACM.

[92] Breunig, M. M., Kriegel, H. P., Ng, R. T., and Sander, J. (2000). LOF: identifying density-based local outliers. In ACM sigmod record, 29(2), 93-104). ACM. (Google Citations: 3563)

[93] Schölkopf, B., Platt, J. C., Shawe-Taylor, J., Smola, A. J., and Williamson, R. C. (2001). Estimating the support of a high-dimensional distribution. Neural Cmputation, 13(7), 1443-1471. (Google Citations: 3715)

[94] He, Z., Xu, X., and Deng, S. (2003). Discovering cluster-based local outliers. Pattern Recognition Letters, 24(9), 1641-1650.

[95] Chandola, V., Banerjee, A., and Kumar, V. (2009). Anomaly detection: A survey. ACM Computing Surveys (CSUR), 41(3), 15.

[96] Yuen, K.V., and Mu, H.Q. (2012). Novel probabilistic method for robust parametric identification and outlier detection. Probabilistic Engineering Mechanics, 30, 48-59.

4.4 Generative adversarial networks

[97] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., & Bengio, Y. (2014). Generative adversarial nets. Advances in Neural Information Processing Systems, 27 (NIPS 2014): 2672-2680. (Google Citations: 2829)

5 Bayesian machine learning

5.1 Bayesian network

[98] Pearl, J. (1985). Bayesian Networks: A Model of Self-Activated Memory for Evidential Reasoning (UCLA Technical Report CSD-850017). Proceedings of the 7th Conference of the Cognitive Science Society, University of California, Irvine, CA. pp. 329334.

[99] Pearl, J. (1988). Probabilistic Reasoning in Intelligent Systems. San Francisco CA: Morgan Kaufmann.

[100] Neapolitan, R. E. (1989). Probabilistic reasoning in expert systems: theory and algorithms. Wiley.

[101] Heckerman, D., Geiger, D., and Chickering, D. M. (1995). Learning Bayesian networks: The combination of knowledge and statistical data. Machine Learning, 20(3), 197-243. (Google citation: 4819)

[102] Heckerman, D. (1997). Bayesian networks for data mining. Data Mining and Knowledge Discovery, 1(1), 79-119.

[103] Friedman, N., Geiger, D., and Goldszmidt, M. (1997). Bayesian network classifiers. Machine Learning, 29(2-3), 131-163.

[104] Friedman, N., Linial, M., Nachman, I., and Pe'er, D. (2000). Using Bayesian networks to analyze expression data. Journal of Computational Biology, 7(3-4), 601-620.

[105] Neapolitan, R. E. (2004). Learning Bayesian networks. Prentice Hall.

[106] Nasrabadi, N. M. (2007). Pattern recognition and machine learning. Journal of Electronic Imaging, 16(4), 049901. (Google citation: 29894)

[107] Yuen, K.V., and Ortiz, G.A. (2016). Bayesian nonparametric general regression. International Journal for Uncertainty Quantification, 6(3), 195-213.

5.2 Bayesian neural network

[108] Kononenko, I. (1989). Bayesian neural networks. Biological Cybernetics, 61(5), 361-370.

[109] Wan, E. A. (1990). Neural network classification: A Bayesian interpretation. IEEE Transactions on Neural Networks, 1(4), 303-305.

[110] MacKay, D. J. (1995). Probable networks and plausible predictionsa review of practical Bayesian methods for supervised neural networks. Network: Computation in Neural Systems, 6(3), 469-505. (Google citation: 827)

[111] MacKay, D. J. (1995). Bayesian neural networks and density networks. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 354(1), 73-80.

[112] Thodberg, H. H. (1996). A review of Bayesian neural networks with an application to near infrared spectroscopy. IEEE Transactions on Neural Networks, 7(1), 56-72.

[113] Barber, D., and Bishop, C. M. (1998). Ensemble Learning in Bayesian Neural Networks. In Neural Networks and Machine Learning, pages 215-237. Springer.

[114] Lampinen, J., and Vehtari, A. (2001). Bayesian approach for neural networksreview and case studies. Neural Networks, 14(3), 257-274.

[115] Neal, R. M. (2012). Bayesian learning for neural networks (Vol. 118). Springer Science and Business Media. (Google citation: 2915)

5.3 Gaussian processes

[116] Barber, D., and Williams, C. K. (1997). Gaussian processes for Bayesian classification via hybrid Monte Carlo. In M. C. Mozer, M. I. Jordan, and T. Petsche, editors, Advances in Neural Information Processing Systems NIPS9, pages 340-346, Cambridge, MA, MIT Press.

[117] MacKay, D. J. (1998). Introduction to Gaussian Processes. In Neural Networks and Machine Learning, volume 168 of NATO advanced study institute on generalization in neural networks and machine learning, pages 133-165. Springer, August.

[118] C. K. I. Williams and D. Barber. (1998) Bayesian classification with Gaussian processes. IEEE Trans Pattern Analysis and Machine Intelligence, 20, 1342-1351.

[119] M. Seeger. (2004) Gaussian Processes for Machine Learning. International Journal of Neural Systems, 14(2), 69-106.

[120] Rasmussen, C. E., and Williams, C. K. (2006). Gaussian processes for machine learning (Vol. 1). Cambridge: MIT press. (Google citation: 1530)

5.4 Relevance vector machine (sparse Bayesian learning)

[121] Tipping, M. E. (2001). Sparse Bayesian learning and the relevance vector machine. Journal of Machine Learning Research, 1(Jun), 211-244. (Google citation: 4949)

[122] Faul, A. C., and Tipping, M. E. (2002). Analysis of sparse Bayesian learning. In Advances in Neural Information Processing Systems (pp. 383-389).

[123] Tipping, M. E., and Faul, A. C. (2003). Fast marginal likelihood maximization for sparse Bayesian models. In AISTATS, January.

[124] Wipf, D. P., and Rao, B. D. (2004). Sparse Bayesian learning for basis selection. IEEE Transactions on Signal processing, 52(8), 2153-2164.

5.5 Bayesian deep learning

[125] Gal, Y., and Ghahramani, Z. (2016). Dropout as a Bayesian approximation: Representing model uncertainty in deep learning. In International Conference on Machine Learning (pp. 1050-1059). (Google citation: 302)

[126] Wang, H., and Yeung, D. Y. (2016). Towards Bayesian deep learning: A framework and some existing methods. IEEE Transactions on Knowledge and Data Engineering, 28(12), 3395-3408.

[127] Wang, H., and Yeung, D. Y. (2016). Towards Bayesian deep learning: A survey. arXiv preprint arXiv:1604.01662.

5.6 Bayesian model class selection and system identification

[128] Raftery, A. E. (1995). Bayesian model selection in social research. Sociological Methodology, 111-163.

[129] Jacobs, R. A., Peng, F., and Tanner, M. A. (1997) A Bayesian approach to model selection in hierarchical mixtures of-experts architectures. Neural Networks, 10(2), 231-241.

[130] Beck, J. L., and Katafygiotis, L. S. (1998). Updating models and their uncertainties. I: Bayesian statistical framework. Journal of Engineering Mechanics, 124(4), 455-461.

[131] Katafygiotis, L. S., and Beck, J. L. (1998). Updating models and their uncertainties. II: Model identifiability. Journal of Engineering Mechanics, 124(4), 463-467.

[132] Wasserman, L. (2000). Bayesian model selection and model averaging. Journal of Mathematical Psychology, 44(1), 92-107.

[133] Corduneanu, A., and Bishop, C. M. (2001). Variational Bayesian Model Selection for Mixture Distributions. In T. Jaakkola and T. Richardson, editors, Artifcial Intelligence and Statistics, pages 27-34. Morgan Kaufmann.

[134] Beck, J. L., and Yuen, K. V. (2004). Model selection using response measurements: Bayesian probabilistic approach. Journal of Engineering Mechanics, 130(2), 192-203. (Google citation: 407)

[135] Posada, D., and Buckley, T. R. (2004). Model selection and model averaging in phylogenetics: advantages of Akaike information criterion and Bayesian approaches over likelihood ratio tests. Systematic Biology, 53(5), 793-808.

[136] Burnham, K. P., and Anderson, D. R. (2004). Multimodel inference: understanding AIC and BIC in model selection. Sociological Methods and Research, 33(2), 261-304. (Google citation: 4977)

[137] Claeskens, G., and Hjort, N. L. (2008). Model selection and model averaging (Vol. 330). Cambridge: Cambridge University Press.

[138] Yuen, K.-V. (2010). Recent developments of Bayesian model class selection and applications in civil engineering. Structural Safety, 32(5), 338346.

5.7 Simulation-based methods for Bayesian inference

(e.g., MCMC, Adaptive MCMC, TMCMC, DREAM, reversible jump MCMC, sequential Monte Carlo, particle filter, BUS)

[139] Metropolis, N., Rosenbluth, A.W., Rosenbluth, M.N., Teller, A.H., and Teller, E. (1953). Equation of state calculations by fast computing machines. Journal of Chemical Physics, 21, 1087-1092. (Google citation: 37307)

[140] Hastings, W. K. (1970). Monte Carlo sampling methods using Markov chains and their applications. Biometrika, 57(1), 97-109. (Google citation: 12113)

[141] Geman, S. and Geman, D. (1984). Stochastic relaxation, Gibbs distribution and the Bayesian restoration of images. IEEE Trans. Pattern Anal. Machine Intell., 6, 721-741.

[142] Gelman, A., and Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. Statistical Science, 457-472.

[143] Gilks, W. R. and P. Wild. (1992). Adaptive rejection sampling for Gibbs sampling. Applied Statistics 41(2), 337348.

[144] Tierney, L. (1994). Markov chains for exploring posterior distributions. the Annals of Statistics, 1701-1728.

[145] Green, P. J. (1995). Reversible jump Markov chain Monte Carlo computation and Bayesian model determination. Biometrika, 82(4), 711-732.

[146] Gelman, A., Roberts, G. O., and Gilks, W. R. (1996). Efficient Metropolis jumping rules. Bayesian Statistics 5, 599608.

[147] MacKay, D.J.C. (1998). Introduction to Monte Carlo methods. In M. Jordan, editor, Learning in graphical models. MIT Press.

[148] Gilks, W. R., Richardson, S., and Spiegelhalter, D. (1998). Markov Chain Monte Carlo in Practice. Boca Raton, FL, Chapman and Hall.

[149] Doucet, A., Godsill, S., and Andrieu, C. (2000). On sequential Monte Carlo sampling methods for Bayesian filtering. Statistics and Computing, 10(3), 197-208.

[150] Doucet, A., De Freitas, N., and Gordon, N. (2001). Sequential Monte Carlo Methods in Practice. New York, Springer.

[151] Doucet, A., Gordon, N. J., and Krishnamurthy, V. (2001). Particle filters for state estimation of jump Markov linear systems. IEEE Transactions on Signal Processing, 49(3), 613-624.

[152] Beck, J. L. and Au, S. K. (2002). Bayesian updating of structural models and reliability using Markov chain Monte Carlo simulation. Journal of Engineering Mechanics-ASCE, 128(4), 380391.

[153] Chopin, N. (2002). A sequential particle filter method for static models. Biometrika, 89(3), 539552.

[154] Arulampalam, M. S., Maskell, S., Gordon, N., and Clapp, T. (2002). A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. IEEE Transactions on Signal Processing, 50(2), 174-188.

[155] Haario, H., Saksman, E., and Tamminen, J. (2005). Componentwise adaptation for high dimensional MCMC. Computational Statistics, 20(2), 265273.

[156] Ter Braak, C. J. (2005). Genetic algorithms and Markov Chain Monte Carlo: Differential Evolution Markov Chain makes Bayesian computing easy (revised) (No. 010404). Wageningen UR, Biometris.

[157] Del Moral, P., Doucet, A., and Jasra, A. (2006). Sequential Monte Carlo samplers. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 68(3), 411436.

[158] Gamerman, D., and Lopes, H. F. (2006). Markov chain Monte Carlo: stochastic simulation for Bayesian inference. CRC Press.

[159] Ter Braak, C. J. (2006). A Markov Chain Monte Carlo version of the genetic algorithm Differential Evolution: easy Bayesian computing for real parameter spaces. Statistics and Computing, 16(3), 239-249.

[160] Ching, J. and Chen, Y. (2007). Transitional Markov chain Monte Carlo method for Bayesian model updating, model class selection, and model averaging. Journal of Engineering Mechanics, 133(7), 816832.

[161] Vrugt, J. A., Ter Braak, C. J. F., Diks, C. G. H., Robinson, B. A., Hyman, J. M., and Higdon, D. (2009). Accelerating Markov chain Monte Carlo simulation by differential evolution with self-adaptive randomized subspace sampling. International Journal of Nonlinear Sciences and Numerical Simulation, 10(3), 273-290.

[162] Vrugt, J. A., and Ter Braak, C. J. (2011). DREAM (D): an adaptive Markov Chain Monte Carlo simulation algorithm to solve discrete, noncontinuous, and combinatorial posterior parameter estimation problems. Hydrology and Earth System Sciences, 15(12).

[163] Laloy, E., and Vrugt, J. A. (2012). Highdimensional posterior exploration of hydrologic models using multipletry DREAM (ZS) and highperformance computing. Water Resources Research, 48(1).

[164] Straub, D., and Papaioannou, I. (2014). Bayesian updating with structural reliability methods. Journal of Engineering Mechanics, 141(3), 04014134.

[165] Betz, W., Papaioannou, I. and Straub, D. (2014). Adaptive variant of the BUS approach to Bayesian updating. Eurodyn 2014. Porto, Portugal

[166] DiazDelaO, F. A., Garbuno-Inigo, A., Au, S. K., and Yoshida, I. (2017). Bayesian updating and model class selection with Subset Simulation. Computer Methods in Applied Mechanics and Engineering, 317, 1102-1121.

[167] Byrnes, P. G., and DiazDelaO, F. A. (2017). Reliability Based Bayesian Inference for Probabilistic Classification: An Overview of Sampling Schemes. In International Conference on Innovative Techniques and Applications of Artificial Intelligence (pp. 250-263). Springer, Cham.

Dongming Zhang / TC309 / 29-04-2022

Reference List for Machine Learning and its Applications in Geotechnical Engineering - PART III: APPLICATIONS IN GEOTECHNICAL ENGINEERING

1 Artificial neural networks

[1] Shahin, M. A., Jaksa, M. B., and Maier, H. R. (2001). Artificial Neural Network Applications in Geotechnical Engineering. Australian Geomechanics, 36(1), 4962.

[2] Shahin, M. A., Jaksa, M. B. and Maier, H. R. (2008). Invited Paper: State of the Art of Artificial Neural Networks in Geotechnical Engineering. Electronic Journal of Geotechnical Engineering, 8, 1-26.

[3] Jaksa, M. B., Maier, H. R. and Shahin, M. A. (2008). Invited Paper: Future Challenges for Artificial Neural Network Modelling in Geotechnical Engineering. Proc. 12th Int. Assoc. for Computer Methods and Advances in Geotech. Engrg. Conference, Goa, India, October 16, 17101719.

[4] Shahin, M. A., Jaksa, M. B. and Maier, H. R. (2009). Invited Paper: Recent Advances and Future Challenges for Artificial Neural Systems in Geotechnical Engineering Applications. Advances in Artificial Neural Systems, Vol. 2009 (2009), Article ID 308239, 9, DOI: 10.1155/2009/308239.

1.1 Site Characterization

[5] Zhou, Y., and Wu, X. (1994). Use of neural networks in the analysis and interpretation of site investigation data. Computer and Geotechnics, 16, 105-122.

[6] Cal, Y. (1995). Soil classification by neural-network. Advances in Engineering Software, 22(2), 95-97.

[7] Basheer, I. A., Reddi, L. N., and Najjar, Y. M. (1996). Site characterization by neuronets: An application to the landfill siting problem. Ground Water, 34, 610-617.

[8] Rizzo, D. M., Lillys, T. P., and Dougherty, D. E. (1996). Comparisons of site characterization methods using mixed data. Geotechnical Special Publication, ASCE, 58(1), 157-179.

[9] Najjar, Y. M., and Basheer, I. A. (1996). Neural network approach for site characterization and uncertainty prediction. Geotechnical Special Publication, ASCE, 58(1), 134-148.

[10] Juang C. H., Jiang T., and Christopher R. A. (2001). Three-dimensional site characterization: neural network approach. Geotechnique, 51(9), 799809.

1.2 Geomaterial Properties and Behavior Modeling

[11] Agrawal, G., Weeraratne, S., and Khilnani, K. (1994). Estimating clay liner and cover permeability using computational neural networks. Proc., First Congress on Computing in Civil Engineering., Washington, June 20-22.

[12] Gribb, M. M., and Gribb, G. W. (1994). Use of neural networks for hydraulic conductivity determination in unsaturated soil. Proc., 2nd Int. Conf. Ground Water Ecology, J. A.

Stanford and H. M. Valett, eds., Bethesda MD: Amer, Water Resources Assoc., 155-163.

[13] Goh, A. T. C. (1995). Modeling soil correlations using neural networks. Journal of Computing in Civil Engineering, ASCE, 9(4), 275-278.

[14] Ellis, G. W., Yao, C., Zhao, R., and Penumadu, D. (1995). Stress-strain modelling of sands using artificial neural networks. Journal of Geotechnical Engineering., ASCE, 121(5), 429-435.

[15] Najjar, Y. M., and Basheer, I. A. (1996). Utilizing computational neural networks for evaluating the permeability of compacted clay liners. Geotechnical and Geological Engineering, 14, 193-221.

[16] Najjar, Y. M., Basheer, I. A., and McReynolds, R. (1996). Neural modeling of Kansan soil swelling. Transportation Research Record, No. 1526, 14-19.

[17] Romero, S., and Pamukcu, S. (1996). Characterization of granular material by low strain dynamic excitation and ANN. Geotechnical Special Publication, ASTM-ASCE, 58(2), 1134-1148.

[18] Penumadu, D., and Jean-Lou, C. (1997). Geomaterial modeling using artificial neural networks. Artificial Neural Networks for Civil Engineers: Fundamentals and Applications, ASCE, 160-184.

[19] Sidarta, D. E., and Ghaboussi, J. (1998). Constitutive modeling of geomaterials from non-uniform material tests. Computers and Geomechanics, 22(10), 53-71.

[20] Ghaboussi, J., and Sidarta, D. E. (1998). New nested adaptive neural networks (NANN) for constitutive modeling. Computers and Geotechnics, 22(1), 29-52.

[21] Zhu, J. H., Zaman, M. M., and Anderson, S. A. (1998). Modeling of soil behavior with a recurrent neural network. Canadian Geotechnical Journal, 35(5), 858-872.

[22] Zhu, J. H., Zaman, M. M., and Anderson, S. A. (1998). Modelling of shearing behavior of a residual soil with recurrent neural network. International Journal of Numerical and Analytical Methods in Geomechanics, 22(8), 671-687.

[23] Penumadu, D., and Zhao, R. (1999). Triaxial compression behavior of sand and gravel using artificial neural networks (ANN). Computers and Geotechnics, 24, 207-230.

1.3 Pile Capacity and Settlement

[24] Goh, A. T. C. (1994). Nonlinear modelling in geotechnical engineering using neural networks. Australian Civil Engineering Transactions, CE36(4), 293-297.

[25] Goh, A. T. C. (1995). Back-propagation neural networks for modeling complex systems. Artificial Intelligence in Engineering, 9, 143-151.

[26] Goh, A. T. C. (1995). Empirical design in geotechnics using neural networks. Géotechnique, 45(4), 709714.

[27] Goh, A. T. C. (1996). Pile driving records reanalyzed using neural networks. Journal of Geotechnical Engineering, ASCE, 122(6), 492-495.

[28] Chan, W. T., Chow, Y. K., and Liu, L. (1995). Neural network: An alternative to pile driving formulas. Computers and Geotechnics, 17, 135-156.

[29] Lee, I. M., and Lee, J. H. (1996). Prediction of pile bearing capacity using artificial neural networks. Computers and Geotechnics, 18(3), 189-200.

[30] Abu-Kiefa, M. A. (1998). General regression neural networks for driven piles in cohesionless soils. Journal of Geotechnical and Geoenvironmental Engineering., ASCE, 124(12), 1177-1185

[31] Teh, C. I., Wong, K. S., Goh, A. T. C., and Jaritngam, S. (1997). Prediction of pile capacity using neural networks. Journal of Computing in Civil Engineering, ASCE, 11(2), 129-138.

[32] Das, S. K., and Basudhar, P. K. (2006). Undrained lateral load capacity of piles in clay using artificial neural network. Computers and Geotechnics, 33(8), 4549.

[33] Shahin, M. A. and Jaksa, M. B. (2009). Intelligent Computing for Predicting Axial Capacity of Drilled Shafts. In Contemporary Topics in In Situ Testing, Analysis, and Reliability of Foundations, Geotechnical Special Publication No. 186, ASCE, pp. 2633.

[34] Pooya Nejad, F. and Jaksa, M. B. (2017). Load-settlement Behavior Modeling of Single Piles Using Artificial Neural Networks and CPT Data. Computers and Geotechnics, Vol. 89, pp. 921.

1.4 Shallow Foundations

[35] Sivakugan, N., Eckersley, J. D., and Li, H. (1998). Settlement predictions using neural networks. Australian Civil Engineering Transactions, CE40, 49-52.

[36] Shahin, M. A., Jaksa, M. B., and Maier, H. R. (2000). Predicting the settlement of shallow foundations on cohesionless soils using back-propagation neural networks. Research Report No. R 167, the University of Adelaide, Adelaide.

[37] Shahin, M. A., Maier, H. R., and Jaksa, M. B. (2002). Predicting Settlements of Shallow Foundations Using Neural Networks. Journal of Geotechnical and Geoenvironmental Engineering, ASCE, 128, (9), 785793.

[38] Shahin, M. A., Jaksa, M. B. and Maier, H. R. (2002). Artificial Neural Network-Based Settlement Prediction Formula for Shallow Foundations on Granular Soils. Austral-ian Geomechanics, 37, (4), 4552.

[39] Shahin, M. A., Maier, H. R. and Jaksa, M. B. (2003). Neural and Neurofuzzy Techniques Applied to Modelling Settlement of Shallow Foundations on Granular Soils. Inter-national Congress on Modelling and Simulation, MODSIM 2003, D. A. Post (ed.), Townsville, July 1417, 4, 18861891.

[40] Shahin, M. A., Maier, H. R. and Jaksa, M. B. (2003). Settlement Prediction of Shallow Foundations on Granular Soils Using B-Spline Neurofuzzy Models. Computers and Geotechnics, 30, (8), 637647.

[41] Shahin, M. A., Maier, H. R., and Jaksa, M. B. (2004). Data division for developing neural networks applied to geotechnical engineering. Journal of Computing in Civil Engineering, 18(2), 105-114.

[42] Shahin, M. A., Jaksa, M. B. and Maier, H. R. (2005). Neural Network Based Stochastic Design Charts for Settlement Prediction. Canadian Geotechnical Journal, 42, (1): 110120.

[43] Shahin, M. A., Jaksa, M. B. and Maier, H. R. (2005). Stochastic Simulation of Settlement Prediction of Shallow Foundations Based on a Deterministic Artificial Neural Network Model. In MODSIM 2005 International Congress on Modelling and Simulation, Zerger, A. and Argent, R.M. (eds), Modelling and Simulation Society of Australia and New Zealand, Melbourne, December 1215, pp. 7378.

[44] Kuo, Y. L., Jaksa, M. B., Lyamin, A. V. and Kaggwa, W. S. (2009). ANN-based Model for Predicting the Bearing Capacity of Strip Footing on Multi-layered Cohesive Soil. Computers and Geotechnics, 36 (3), 503516.

1.5 Tensile Capacity of Anchors

[45] Shahin, M. A. and Jaksa, M. B. (2004). Probabilistic Assessment of the Uncertainty Associated with the Pullout Capacity of Marquee Anchors. Proc. 9th Australia New Zealand Conference on Geomechanics, Auckland, February 911, Vol. 2, pp. 917921.

[46] Shahin, M. A. and Jaksa, M. B. (2005). Neural Network

Prediction of Pullout Capacity of Marquee Ground Anchors. Computers and Geotechnics, 32(3), 153163.

[47] Shahin, M. A. and Jaksa, M. B. (2005). Modelling the Pullout Capacity of Marquee Ground Anchors Using Neuro-fuzzy Technique. In MODSIM 2005 International Congress on Modelling and Simulation, Zerger, A. and Argent, R.M. (eds),

Modelling and Simulation Society of Australia and New Zealand, Melbourne, December 1215, pp. 6672.

[48] Shahin, M. A. and Jaksa, M. B. (2006). Pullout Capacity of Small Ground Anchors by Direct CPT Methods and Neural Networks. Canadian Geotechnical Journal, 43(6), 626637.

1.6 Liquefaction

[49] Goh, A. T. C. (1994). Seismic liquefaction potential assessed by neural network. Journal of Geotechnical and Geoenvironmental Engineering, ASCE, 120(9), 1467-1480.

[50] Goh, A. T. C. (1996). Neural-network modeling of CPT seismic liquefaction data. Journal of Geotechnical Engineering, ASCE, 122(1), 70-73.

[51] Najjar, Y. M., and Ali, H. E. (1998). CPT-based liquefaction potential assessment: A neuronet approach. Geotechnical Special Publication, ASCE, 1, 542-553

[52] Agrawal, G., Chameau, J. A., and Bourdeau, P. L. (1997). Assessing the liquefaction susceptibility at a site based on information from penetration testing. In Artificial neural networks for civil engineers: fundamentals and applications, N. Kartam, I. Flood, and J. H. Garrett, eds., New York, 185-214.

[53] Juang, C. H., and Chen, C. J. (1999). CPT-based liquefaction evaluation using artificial neural networks. Com-puter Aided Civil and Infrastructure Engineering, 14(3), 221-229.

[54] Goh A. T. C. (2002). Probabilistic neural network for evaluating seismic liquefaction potential. Canadian Geotechnical Journal, 39(2), 21932.

1.7 Soil Retaining Structures

[55] Goh, A. T. C., Wong, K. S., and Broms, B. B. (1995). Estimation of lateral wall movements in braced excavation using neural networks. Canadian Geotechnical Journal, 32, 1059-1064.

1.8 Slope Stability

[56] Ni, S. H., Lu, P. C., and Juang, C. H. (1996). A fuzzy neural network approach to evaluation of slope failure potential. Microcomputers in Civil Engineering, 11, 59-66.

[57] Chok, Y. H., Jaksa, M. B., Kaggwa W. S., Griffiths, D. V. and Fenton, G. A. (2016). Neural Network Prediction of the Reliability of Heterogeneous Cohesive Slopes. International Journal for Numerical & Analytical Methods in Geomechanics, 40, 11:1556-1569.

1.9 Tunnels and Underground Openings

[58] Lee, C., and Sterling, R. (1992). Identifying probable failure modes for underground openings using a neural network. International Journal Rock Mechanics and Mining Science and Geomechanics Abstracts, 29(1), 49-67.

[59] Sterling, R. L., and Lee, C. A. (1992). A neural network - expert system hybrid approach for tunnel design. Proc., 33rd United-States Symp. Rock Mechanics, J. R. Tillerson and W. R. Wawerisk, eds., Brookfield VT: Balkema, 501-510.

[60] Moon, H. K., Na, S. M., and Lee, C. W. (1995). Artificial neural-network integrated with expert-system for preliminary design of tunnels and slopes. Proc., 8th Int. Congress on Rock Mechanics, T. Fujii, ed., Rotterdam: Balkema, 1 and 2, 901-905.

[61] Shi, J. J., Ortigao, J. A. R., and Bai, J. (1998). Modular neural networks for predicting settlement during tunneling. Journal of Geotechnical and Geoenvironmental Engineering, ASCE, 124(5), 389-395.

[62] Shi, J. J. (2000). Reducing prediction error by transforming I nput data for neural networks. Journal of Computing in Civil Engineering, ASCE, 14(2), 109-116.

1.10 Ground Improvement

[63] Ranasinghe, R. A. T. M., Jaksa, M. B., Kuo, Y. L. and Pooya Nejad, F. (2017). Application of Artificial Neural Networks for Predicting the Impact of Rolling Dynamic Com-paction Using Dynamic Cone Penetrometer Test Results. Journal of Rock Mechanics and Geotechnical Engineer-ing, 9(2), 340349.

[64] Ranasinghe, R. A. T. M., Jaksa, M. B., Pooya Nejad, F. and Kuo, Y. L. (2017). Predicting the Effectiveness of Rolling Dynamic Compaction Using Genetic Programming and Cone Penetration Test Data. Proc. of Institution of Civil Engineers Ground Improvement, 170(4), 193207.

2 Support vector machine

2.1 Site Characterization

[65] Odeh, I. O. A., Chittleborough, D. J., and McBratney, A. B. (1992). Soil pattern recognition with fuzzy-c-means: application to classification and soil-landform interrelationships. Soil Science Society of America Journal, 56(2), 505-516.

[66] Bhattacharya, B., and Solomatine, D. P. (2006). Machine learning in soil classification. Neural Networks, 19(2), 186-195.

[67] Sitharam, T. G., Samui, P., and Anbazhagan, P. (2008). Spatial variability of rock depth in Bangalore using geostatistical, neural network and support vector machine models. Geotechnical and Geological Engineering, 26(5), 503-517.

[68] Yu, L., Porwal, A., Holden, E. J., and Dentith, M. C. (2012). Towards automatic lithological classification from remote sensing data using support vector machines. Com-puters and Geosciences, 45, 229-239.

2.2 Geomaterial Properties and Behavior Modeling

[69] Feng, X. T., Zhao, H., and Li, S. (2004). A new displacement back analysis to identify mechanical geomaterial parameters based on hybrid intelligent methodology. International Journal for Numerical and Analytical Methods in Geomechanics, 28(11), 1141-1165.

[70] Zhao, H. B., and Yin, S. (2009). Geomechanical parameters identification by particle swarm optimization and support vector machine. Applied Mathematical Modelling, 33 (10), 3997-4012.

[71] Tinoco, J., Correia, A. G., and Cortez, P. (2011). A data mining approach for predicting jet grouting geomechanical parameters. In Road Materials and New Innovations in Pavement Engineering (pp. 97-104).

[72] Ceryan, N., Okkan, U., Samui, P., and Ceryan, S. (2013). Modeling of tensile strength of rocks materials based on support vector machines approaches. International Journal for Numerical and Analytical Methods in Geomechan-ics, 37(16), 2655-2670.

[73] Ceryan, N. (2014). Application of support vector machines and Bayesian neural network machines in predicting uniaxial compressive strength of volcanic rocks. Journal of African Earth Sciences, 100, 634-644.

2.3 Pile Capacity

[74] Samui, P. (2008). Prediction of friction capacity of driven piles in clay using the support vector machine. Canadian Geotechnical Journal, 45(2), 288-295.

[75] Pal, M., and Deswal, S. (2008). Modeling pile capacity using support vector machines and generalized regression neural network. ASCE Journal of Geotechnical and Geoenviron-mental Engineering, 134(7), 1021-1024.

[76] Samui, P. (2011). Prediction of pile bearing capacity using support vector machine. International Journal of Geotechnical Engineering, 5(1), 95-102.

[77] Tinoco, J., Correia, A. G., and Cortez, P. (2014). Support vector machines applied to uniaxial compressive strength prediction of jet grouting columns. Computers and Geotechnics, 55, 132-140.

[78] Kordjazi, A., Nejad, F. P., and Jaksa, M. B. (2014). Prediction of ultimate axial load-carrying capacity of piles using a support vector machine based on CPT data. Computers and Geotechnics, 55, 91-102.

[79] Kordjazi, A., Pooya Nejad, F. and Jaksa, M. B. (2014). Prediction of Ultimate Bearing Capacity of Axially Loaded Piles Using a Support Vector Machine Based on CPT Data. Computers and Geotechnics, 55, (1), 91102.

[80] Kordjazi, A., Pooya Nejad, F. and Jaksa, M. B. (2015). Prediction of Load-carrying Capacity of Piles Using a Support Vector Machine and Improved Data Collection. Proc. 12th Australia New Zealand Conference on Geomechanics, ANZ 2015, Wellington, February 2225, 8 pp.

2.4 Settlement of Foundations

[81] Samui, P., and Sitharam, T. G. (2008). Leastsquare support vector machine applied to settlement of shallow foundations on cohesionless soils. International Journal for Numerical and Analytical Methods in Geomechanics, 32(17), 2033-2043.

[82] Samui, P. (2008). Support vector machine applied to settlement of shallow foundations on cohesionless soils. Computers and Geotechnics, 35(3), 419-427.

2.5 Liquefaction

[83] Pal, M. (2006). Support vector machinesbased modelling of seismic liquefaction potential. International Journal for Numerical and Analytical Methods in Geomechanics, 30(10), 983-996.

[84] Pal, M. (2006). Support vector machinesbased modelling of seismic liquefaction potential. International Journal for Numerical and Analytical Methods in Geomechanics, 30(10), 983-996.

[85] Goh, A. T., and Goh, S. H. (2007). Support vector machines: their use in geotechnical engineering as illustrated using seismic liquefaction data. Computers and Geotechnics, 34(5), 410-421.

[86] Samui, P., and Karthikeyan, J. (2013). Determination of liquefaction susceptibility of soil: a least square support vector machine approach. International Journal for Numerical and Analytical Methods in Geomechanics, 37(9), 1154-1161.

2.6 Soil Retaining Walls and Dams

[87] Zheng, D., Cheng, L., Bao, T., and Lv, B. (2013). Integrated parameter inversion analysis method of a CFRD based on multi-output support vector machines and the clonal selection algorithm. Computers and Geotechnics, 47, 68-77.

[88] Ji, Z., Wang, B., Deng, S., and You, Z. (2014). Predicting dynamic deformation of retaining structure by LSSVR-based time series method. Neurocomputing, 137, 165-172.

[89] Rankovi, V., Grujovi, N., Divac, D., and Milivojevi, N. (2014). Development of support vector regression identification model for prediction of dam structural behaviour. Structural Safety, 48, 33-39.

[90] Fisher, W. D., Camp, T. K., and Krzhizhanovskaya, V. V. (2016). Crack detection in earth dam and levee passive seismic data using support vector machines. Procedia Computer Science, 80, 577-586.

2.7 Slope Stability

[91] Feng, X. T., Zhao, H., and Li, S. (2004). Modeling nonlinear displacement time series of geo-materials using evolutionary support vector machines. International Journal of Rock Mechanics and Mining Sciences, 41(7), 1087-1107.

[92] Samui, P. (2008). Slope stability analysis: a support vector machine approach. Environmental Geology, 56(2), 255.

[93] Zhao, H. B. (2008). Slope reliability analysis using a support vector machine. Computers and Geotechnics, 35(3), 459-467.

[94] Tan, X. H., Bi, W. H., Hou, X. L., and Wang, W. (2011). Reliability analysis using radial basis function networks and support vector machines. Computers and Geotechnics, 38 (2), 178-186.

[95] Li, S., Zhao, H. B., and Ru, Z. (2013). Slope reliability analysis by updated support vector machine and Monte Carlo simulation. Natural Hazards, 65(1), 707-722.

[96] Samui, P., Lansivaara, T., and Bhatt, M. R. (2013). Least square support vector machine applied to slope reliability analysis. Geotechnical and Geological Engineering, 31(4), 1329-1334.

[97] Li, B., Li, D., Zhang, Z., Yang, S., and Wang, F. (2015). Slope stability analysis based on quantum-behaved particle swarm optimization and least squares support vector machine. Applied Mathematical Modelling, 39(17), 5253-5264.

[98] Kang, F., and Li, J. (2015). Artificial bee colony algorithm optimized support vector regression for system reliability analysis of slopes. Journal of Computing in Civil Engineering, 30(3), 04015040.

[99] Kang, F., Li, J. S., and Li, J. J. (2016). System reliability analysis of slopes using least squares support vector machines with particle swarm optimization. Neurocomputing, 209, 46-56.

[100] Kang, F., Xu, Q., and Li, J. J. (2016). Slope reliability analysis using surrogate models via new support vector machines with swarm intelligence. Applied Mathematical Modelling, 40(11), 6105-6120.

[101] Li, S., Zhao, H., Ru, Z., and Sun, Q. (2016). Probabilistic back analysis based on Bayesian and multi-output support vector machine for a high cut rock slope. Engineering Geology, 203, 178-190.

2.8 Tunnels and Underground Openings

[102] Yao, B. Z., Yang, C. Y., Yao, J. B., and Sun, J. (2010). Tunnel surrounding rock displacement prediction using support vector machine. International Journal of Computational Intelligence Systems, 3(6), 843-852.

[103] Jiang, A. N., Wang, S. Y., and Tang, S. L. (2011). Feedback analysis of tunnel construction using a hybrid arithmetic based on support vector machine and particle swarm optimization. Automation in Construction, 20(4), 482-489.

[104] Zhou, J., Li, X., and Shi, X. (2012). Long-term predicttion model of rockburst in underground openings using heuristic algorithms and support vector machines. Safety Science, 50(4), 629-644.

[105] Mahdevari, S., Haghighat, H. S., and Torabi, S. R. (2013). A dynamically approach based on SVM algorithm for prediction of tunnel convergence during excavation. Tunnelling and Underground Space Technology, 38, 59-68.

[106] Mahdevari, S., Shahriar, K., Yagiz, S., and Shirazi, M. A. (2014). A support vector regression model for predicting tunnel boring machine penetration rates. International Journal of Rock Mechanics and Mining Sciences, 72, 214-229.

[107] Li, X., Li, X., and Su, Y. (2016). A hybrid approach combining uniform design and support vector machine to probabilistic tunnel stability assessment. Structural Safety, 61, 22-42.

2.9 Landslide

[108] Feng, X. T., Hudson, J. A., Li, S., Zhao, H., Gao, W., and Zhang, Y. (2004). Integrated intelligent methodology for large-scale landslide prevention design. International Journal of Rock Mechanics and Mining Sciences, 41, 750-755.

[109] Yao, X., Tham, L. G., and Dai, F. C. (2008). Landslide susceptibility mapping based on support vector machine: a case study on natural slopes of Hong Kong, China. Geomorphology, 101(4), 572-582.

[110] Kavzoglu, T., and Colkesen, I. (2009). A kernel functions analysis for support vector machines for land cover classification. International Journal of Applied Earth Observation and Geoinformation, 11(5), 352-359.

[111] Marjanovic, M., Bajat, B., and Kovacevic, M. (2009). Landslide susceptibility assessment with machine learning algorithms. In Intelligent Networking and Collaborative Systems, 2009. INCOS'09. International Conference on (pp. 273-278). IEEE.

[112] Marjanovi, M., Kovaevi, M., Bajat, B., and Voenílek, V. (2011). Landslide susceptibility assessment using SVM machine learning algorithm. Engineering Geology, 123(3), 225-234.

[113] Xu, C., Dai, F., Xu, X., and Lee, Y. H. (2012). GIS-based support vector machine modeling of earthquake-triggered landslide susceptibility in the Jianjiang River watershed, China. Geomorphology, 145, 70-80.

[114] Bui, D. T., Pradhan, B., Lofman, O., and Revhaug, I. (2012). Landslide susceptibility assessment in vietnam using support vector machines, decision tree, and Naive Bayes Models. Mathematical Problems in Engineering, 2012.

[115] Ballabio, C., and Sterlacchini, S. (2012). Support vector machines for landslide susceptibility mapping: the Staffora River Basin case study, Italy. Mathematical Geosci-ences, 44(1), 47-70.

[116] Pourghasemi, H. R., Jirandeh, A. G., Pradhan, B., Xu, C., and Gokceoglu, C. (2013). Landslide susceptibility mapping using support vector machine and GIS at the Gole-stan Province, Iran. Journal of Earth System Science, 122(2), 349-369.

[117] Li, X. Z., and Kong, J. M. (2014). Application of GASVM method with parameter optimization for landslide development prediction. Natural Hazards and Earth System Sciences, 14(3), 525-533.

[118] Bui, D. T., Tuan, T. A., Klempe, H., Pradhan, B., and Revhaug, I. (2016). Spatial prediction models for shallow landslide hazards: a comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree. Landslides, 13(2), 361-378.

[119] Hong, H., Pradhan, B., Jebur, M. N., Bui, D. T., Xu, C., and Akgun, A. (2016). Spatial prediction of landslide hazard at the Luxi area (China) using support vector machines. Environmental Earth Sciences, 75(1), 40.

3 Clustering

3.1 Site Characterization

[120] Judd, A. G. (1980). The use of cluster analysis in the derivation of geotechnical classifications. Bulletin of the Association of Engineering Geologists, 17(4), 193-211.

[121] Hegazy, Y. A. (1998). Delineating Geostratigraphy by Cluster Analysis of Piezocone Data. Ph. D Thesis, Georgia Institute of Technology, 464 pp.

[122] Hegazy, Y. A., and Mayne, P. W. (2002). Objective site characterization using clustering of piezocone data. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 128(12), 986-996.

[123] Facciorusso, J., and Uzielli, M. (2004). Stratigraphic profiling by cluster analysis and fuzzy soil classification from mechanical cone penetration tests. In Geotechnical and Geophysical Site Characterization (Proceedings ISC-2, Portugal), pp. 905-912, (Millpress: Rotterdam).

[124] Facciorusso, J., and Uzielli, M. (2004). Stratigraphic profiling by cluster analysis and fuzzy soil classification from mechanical cone penetration tests. Proc. of ISC-2 on Geotechnical and Geophysical Site Characterization, Porto, Millpress, Rotterdam, 905-912.

[125] Das, S. K., and Basudhar, P. K. (2009). Utilization of self-organizing map and fuzzy clustering for site characterization using piezocone data. Computers and Geotechnics, 36(1-2), 241-248.

[126] Walvoort, D. J. J., Brus, D. J., and De Gruijter, J. J. (2010). An R package for spatial coverage sampling and random sampling from compact geographical strata by k-means. Computers and Geosciences, 36(10), 1261-1267.

[127] Ferentinou, M. D., Hasiotis, T., and Sakellariou, M. G. (2010). Clustering of Geotechnical Properties of Marine Sediments Through SelfOrganizing Maps: An Example from the Zakynthos CanyonValley System, Greece. In Submarine Mass Movements and Their Consequences (pp. 43-54). Springer, Dordrecht.

[128] Bashari, A., Beiki, M., and Talebinejad, A. (2011). Estimation of deformation modulus of rock masses by using fuzzy clustering-based modeling. International Journal of Rock Mechanics and Mining Sciences, 48(8), 1224-1234.

[129] Ferentinou, M., Hasiotis, T., and Sakellariou, M. (2012). Application of computational intelligence tools for the analysis of marine geotechnical properties in the head of Zakynthos canyon, Greece. Computers and Geosciences, 40, 166-174.

[130] Riquelme, A. J., Abellán, A., Tomás, R., and Jaboyedoff, M. (2014). A new approach for semi-automatic rock mass joints recognition from 3D point clouds. Computers and Geosciences, 68, 38-52.

[131] Masoud, A. A. (2016). Geotechnical site suitability mapping for urban land management in Tanta District, Egypt. Arabian Journal of Geosciences, 9(5), 340.

3.2 Liquefaction

[132] Garcia, S. R., Romo, M. P., and Botero, E. (2008). A neurofuzzy system to analyze liquefaction-induced lateral spread. Soil Dynamics and Earthquake Engineering, 28(3), 169-180.

3.3 Slope Stability

[133] Tang, X. S., Li, D. Q., Chen, Y. F., Zhou, C. B., and Zhang, L. M. (2012). Improved knowledge-based clustered partitioning approach and its application to slope reliability analysis. Computers and Geotechnics, 45, 34-43.

3.4 Lifeline Engineering

[134] Toprak, S., Nacaroglu, E., Cetin, O. A., and Koc, A. C. (2009). Pipeline damage assessment using cluster analysis. In TCLEE 2009: Lifeline Earthquake Engineering in a Multihazard Environment (pp. 1-8).

[135] Jayaram, N., and Baker, J. W. (2010). Efficient sampling and data reduction techniques for probabilistic seismic lifeline risk assessment. Earthquake Engineering and Structural Dynamics, 39(10), 1109-1131.

[136] Sun, J., Wang, R., Wang, X., Yang, H., and Ping, J. (2014). Spatial cluster analysis of bursting pipes in water supply networks. Procedia Engineering, 70, 1610-1618.

[137] Lim, H. W., Song, J., and Kurtz, N. (2015). Seismic reliability assessment of lifeline networks using clustering-based multiscale approach. Earthquake Engineering and Structural Dynamics, 44(3), 355-369.

3.5 Landslide

[138] Gorsevski, P. V., Gessler, P. E., and Jankowski, P. (2003). Integrating a fuzzy k-means classification and a Bayesian approach for spatial prediction of landslide hazard. Journal of Geographical Systems, 5(3), 223-251.

[139] Alimohammadlou, Y., Najafi, A., and Gokceoglu, C. (2014). Estimation of rainfall-induced landslides using ANN and fuzzy clustering methods: a case study in Saeen Slope, Azerbaijan province, Iran. Catena, 120, 149-162.

[140] Melchiorre, C., Matteucci, M., Azzoni, A., and Zanchi, A. (2008). Artificial neural networks and cluster analysis in landslide susceptibility zonation. Geomorphology, 94(3-4), 379-400.

[141] Ding, M., and Hu, K. (2014). Susceptibility mapping of landslides in Beichuan County using cluster and MLC methods. Natural Hazards, 70(1), 755-766.

4 Feature learning (Dimensionality reduction)

4.1 Soil Retaining Walls

[142] Hashash, Y. M., Levasseur, S., Osouli, A., Finno, R., and Malecot, Y. (2010). Comparison of two inverse analysis techniques for learning deep excavation response. Computers and Geotechnics, 37(3), 323-333.

4.2 Slope Stability

[143] He, H., Li, S., Sun, H., and Yang, T. (2011). Environmental factors of road slope stability in mountain area using principal component analysis and hierarchy cluster. Environmental Earth Sciences, 62(1), 55-59.

[144] Crosta, G. B., Frattini, P., and Agliardi, F. (2013). Deep seated gravitational slope deformations in the European Alps. Tectonophysics, 605, 13-33.

4.3 Tunnels and Underground Openings

[145] Yun, H. B., Park, S. H., Mehdawi, N., Mokhtari, S., Chopra, M., Reddi, L. N., and Park, K. T. (2014). Monitoring for close proximity tunneling effects on an existing tunnel using principal component analysis technique with limited sensor data. Tunnelling and Underground Space Technology, 43, 398-412.

4.4 Landslide

[146] Micheletti, N., Foresti, L., Robert, S., Leuenberger, M., Pedrazzini, A., Jaboyedoff, M., and Kanevski, M. (2014). Machine learning feature selection methods for landslide susceptibility mapping. Mathematical Geosciences, 46(1), 33-57.

4.5 Offshore Engineering

[147] Spaulding, M. L., Grilli, A., Damon, C., and Fugate, G. (2010). Application of technology development index and principal component analysis and cluster methods to ocean renewable energy facility siting. Marine Technology Society Journal, 44(1), 8-23.

4.6 Others

[148] Blatman, G., and Sudret, B. (2008). Sparse polynomial chaos expansions and adaptive stochastic finite elements using a regression approach. Comptes Rendus Mécanique, 336(6), 518-523.

[149] Blatman, G., and Sudret, B. (2011). Adaptive sparse polynomial chaos expansion based on least angle regression. Journal of Computational Physics, 230(6), 2345-2367.

[150] Blatman, G., and Sudret, B. (2010). An adaptive algorithm to build up sparse polynomial chaos expansions for stochastic finite element analysis. Probabilistic Engineering Mechanics, 25(2), 183-197.

5 Outlier detection

5.1 Site Characterization

[151] Halim, I. S., and Tang, W. H. (1993). Site exploration strategy for geologic anomaly characterization. Journal of geotechnical engineering, 119(2), 195-213.

[152] Kim, H. S., Chung, C. K., and Kim, H. K. (2016). Geospatial data integration for subsurface stratification of dam site with outlier analyses. Environmental Earth Sciences, 75(2), 168.

5.2 Others

[153] Yuen, K.V., and Ortiz, G.A. (2017). Outlier detection and robust regression for correlated data. Computer Methods in Applied Mechanics and Engineering, 313, 632-646.

6 Bayesian machine learning

6.1 Site Characterization

[154] Tang, W. H. (1971). A Bayesian evaluation of information for foundation engineering design. In Proc., 1st International Conf. on Applications of Statistics and Probability to Soil and Structural Engineering, Hong Kong.

[155] Tang, W. H. (1987). Updating anomaly statistics - single anomaly case. Structural Safety, 4(2), 151-163.

[156] Nobre, M. M. and Sykes, J. F. (1992). Application of Bayesian Kriging to subsurface characterization. Canadian Geotechnical Journal, 29(4): 589-598.

[157] Honjo, Y., and Kudo, N. (1998). Matching objective and subjective information in geotechnical inverse analysis based on entropy minimization. Proc. International Symp. on Inverse Problems in Engineering Mechanics, Nagano, Japan, 263--271.

[158] McGrath, T. and Gilbert, R. (1999). Analytical method for designing and analyzing 1D search programs. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 125(12), 1043-1056.

[159] Ditlevsen, O., Tarp-Johansen, N. J. and Denver, H. (2000). Bayesian soil assessments combining prior with posterior censored samples. Computers and Geotechnics, 26(3-4), 187-198.

[160] Zhang, L. M., Tang, W. H., Zhang, L. L., and Zheng, J. G., (2004). Reducing uncertainty of prediction from empirical correlations. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 130(5), 526-534.

[161] Jung, B. C., Gardoni, P., Biscontin, A. (2008). Probabilistic soil identification based on cone penetration tests. Geotechnique, 58(7), 591-603.

[162] Cetin, K. and Ozan, C. (2009). CPT-Based Probabilistic Soil Characterization and Classification. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 135(1), 84-107.

[163] Ching, J., Phoon, K. K., and Chen, Y. C., (2010). Reducing shear strength uncertainties in clays by multivariate correlations. Canadian Geotechnical Journal, 47 (1), 1633.

[164] Wang, Y., Au, S. K. and Cao, Z. J. (2010). Bayesian approach for probabilistic characterization of sand friction angles. Engineering Geology, 114 (34), 354363.

[165] Ching, J., Chen, J. R., Yeh, J. Y., and Phoon, K. K., (2012). Updating uncertainties in friction angles of clean sands. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 138 (2), 217229.

[166] Houlsby, N. M. T. and Houlsby, G. T. (2013). Statistical fitting of undrained strength data. Geotechnique, 63(14), 1253-1263.

[167] Uzielli, M. and Mayne, P. W. (2013). Bayesian characterization of transformation uncertainty for strength and stiffness of sands. Foundation Engineering in the Face of Uncertainty: Honoring Fred H. Kulhawy (GSP 229), ASCE, Reston, VA, 368-384.

[168] Wang, Y. and Cao, Z. J. (2013) Probabilistic characterization of Youngs modulus of soil using equivalent samples. Engineering Geology, 159, 106118.

[169] Cao, Z. J. and Wang, Y. (2013) Bayesian approach for probabilistic site characterization using cone penetration tests. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 139 (2), 267276.

[170] Wang, Y., Huang, K. and Cao, Z. J. (2013) Probabilistic identification of underground soil stratification using cone penetration tests. Canadian Geotechnical Journal, 50 (7), 766776.

[171] Cao, Z. J. and Wang, Y. (2014) Bayesian model comparison and selection of spatial correlation functions for soil parameters. Structural Safety, 49, 1017.

[172] Cao, Z. J., Huang, K., and Wang, Y. (2014). Bayesian inverse analysis for geotechnical site characterization using cone penetration test. International Journal of Reliability and Safety, 8(2-4), 97-116.

[173] Cao, Z. J. and Wang, Y. (2014) Bayesian model comparison and characterization of undrained shear strength. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 140 (6), 04014018, 19.

[174] Feng, X. and Jimenez, R. (2014). Bayesian prediction of elastic modulus of intact rocks using their uniaxial compressive strength. Engineering Geology, 173(1), 32-40.

[175] Müller, R., Larsson, S. and Spross, J. (2014). Extended multivariate approach for uncertainty reduction in the assessment of undrained shear strength in clays. Canadian Geotechnical Journal, 51(3), 231-245.

[176] Wang, Y., Huang, K. and Cao, Z. J. (2014) Bayesian identification of soil strata in London Clay. Geotechnique, 64 (3), 239246.

[177] Wang, Y., Zhao, T. Y. and Cao, Z. J. (2015) Site-specific probability distribution of geotechnical properties. Computers and Geotechnics, 70, 159168.

[178] Wang, Y. and Aladejare, A. E. (2015). Selection of site-specific regression model for characterization of uniaxial compressive strength of rock. International Journal of Rock Mechanics and Mining Sciences, 75, 73-81.

[179] Ching, J., Wu, S. S., and Phoon, K. K. (2015). Statistical characterization of random field parameters using frequentist and Bayesian approaches. Canadian Geotechnical Journal, 53(2), 285-298.

[180] Cao, Z. J., Wang, Y. and Li, D. Q. (2016). Quantification of prior knowledge in geotechnical site characterization. Engineering Geology, 203, 107116.

[181] Cao, Z. J., Wang, Y., and Li, D. Q. (2016). Site-specific characterization of soil properties using multiple measurements from different test procedures at different locations - A Bayesian sequential updating approach. Engineering Geology, 211, 150-161.

[182] Ching, J., and Wang, J. S. (2016). Application of the transitional Markov chain Monte Carlo to probabilistic site characterization. Engineering Geology, 203, 151167.

[183] Wang, Y. and Aladejare, A. E. (2016). Bayesian characterization of correlation between uniaxial compressive strength and Youngs modulus of rock. International Journal of Rock Mechanics and Mining Sciences, 85, 1019.

[184] Wang, Y. and Akeju, O. V. (2016). Quantifying the cross-correlation between effective cohesion and friction angle of soil from limited site-specific data. Soils and Foun-dations, 56(6), 10571072.

[185] Wang, Y., Akeju, O. V., and Cao, Z. J. (2016). Bayesian Equivalent Sample Toolkit (BEST): an Excel VBA program for probabilistic characterisation of geotechnical properties from limited observation data. Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, 10(4), 251-268.

[186] Wang, Y., Cao, Z. J. and Li, D. Q. (2016). Bayesian perspective on geotechnical variability and site characterization. Engineering Geology, 203, 117125.

[187] Wang, Y. and Zhao, T. (2016). Interpretation of soil property profile from limited measurement data: a compressive sampling perspective. Canadian Geotechnical Journal, 53(9), 1547-1559.

[188] Wang, Y. and Aladejare, A. E. (2016). Evaluating variability and uncertainty of Geological Strength Index at a specific site. Rock Mechanics and Rock Engineering, 49(9), 35593573.

[189] Tian, M., Li, D. Q., Cao, Z. J., Phoon, K. K., and Wang, Y. (2016). Bayesian identification of random field model using indirect test data. Engineering Geology, 210, 197-211.

[190] Wang, Y. and Aladejare, A. E. (2016). Evaluating variability and uncertainty of Geological Strength Index at a specific site. Rock Mechanics and Rock Engineering, 49(9), 35593573.

[191] Akeju, O. V., Senetakis, K., and Wang, Y. (2017). Bayesian parameter identification and model selection for normalized modulus reduction curves of soils. Journal of Earthquake Engineering, 1-29.

[192] Aladejare, A. E., and Wang, Y. (2017). Sources of uncertainty in site characterization and their impact on geotechnical reliability-based design. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 3(4), 04017024.

[193] Ching, J. and Phoon, K. K. (2017). Characterizing uncertain site-specific trend function by sparse Bayesian learning, ASCE Journal of Engineering Mechanics, 143(7), 04017028.

[194] Wang, Y., Akeju, O. V., and Zhao, T. (2017). Interpolation of spatially varying but sparsely measured geo-data: A comparative study. Engineering Geology, 231, 200-217.

[195] Wang, Y., Arroyo, M., Cao, Z. J., Ching, J., Länsivaara, T., Orr, T., and Simpson, B. (2017). Selection of characteristic values for rock and soil properties using Bayesian statistics and prior knowledge. Joint TC205/TC304 Working Group on Discussion of statistical/reliability methods for Eurocodes, ISSMGE.

[196] Wang, Y. and Zhao, T. (2017). Statistical interpretation of soil property profiles from sparse data using Bayesian Compressive Sampling. Geotechnique, 67(6), 523-536.

[197] Wang, Y. and Zhao, T. (2017). Bayesian assessment of site-specific performance of geotechnical design charts with unknown model uncertainty. International Journal for Numerical and Analytical Methods in Geomechanics, 41(5), 781-800.

[198] Aladejare, A. E. and Wang, Y. (2017). Evaluation of rock property variability. Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, 11(1), 22-41.

[199] Zhao, T., Montoya-Noguera, S., Phoon, K. K., and Wang, Y. (2018). Interpolating spatially varying soil property values from sparse data for facilitating characteristic value selection. Canadian Geotechnical Journal, 55(2), 171-181.

[200] Huang, J., Zheng, D., Li, D., Kelly, R., and Sloan, S. W. (2017). Probabilistic characterization of 2D soil profile by integrating CPT with MASW data. Canadian Geotechnical Journal, 10.1139/cgj-2017-0429.

[201] Ching, J., Phoon, K. K., Beck, J. L., and Huang, Y., (2018). Identifiability of Geotechnical Site-Specific Trend Functions, ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 2017, 3 (4): 04017021.

[202] Ching, J., Wu, T., Stuedlein, A., and Bong, T. (2018) Estimating horizontal scale of fluctuation with limited CPT soundings. Geoscience Frontiers, 10.1016/j.gsf.2017.11.008.

[203] Shen, M. Y., Cao, Z. J., Li, D. Q., and Wang, Y. (2018). Probabilistic characterization of site-specific inherent variability of undrained shear strength using both indirect and direct measurements. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 4(1), 04017038.

[204] Wang, L., Cao, Z. J., Li, D. Q., Phoon, K. K., and Au, S. K. (2018). Determination of site-specific soil-water characteristic curve from a limited number of test data-A Bayesian perspective, Geoscience Frontiers, 10.1016/j.gsf.2017.10.014.

[205] Zhang, L., Li, D. Q., Tang, X. S., Cao, Z. J., and Phoon, K. K. (2018). Bayesian model comparison and characterization of bivariate distribution for shear strength parameters of soil. Computers and Geotechnics, 95, 110-118.

[206] Wang, Y., Zhao, T., and Phoon, K. K. (2018). Direct simulation of random field samples from sparsely measured geotechnical data with consideration of uncertainty in interpretation. Canadian Geotechnical Journal, https://doi.org/10.1139/cgj-2017-0254.

6.2 Pile Capacity

[207] Baecher, G. R. and Rackwitz, R. (1982). Factors of safety and pile load tests. International Journal for Numerical and Analytical Methods in Geomechanics, 6(4), 609-624.

[208] Najjar, S. and Gilbert, R. (2009). Importance of Lower-Bound Capacities in the Design of Deep Foundations. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 135(7), 890-900.

[209] Park, J. H., Kim, D. and Chung, C. K. (2012). Implementation of Bayesian theory on LRFD of axially loaded driven piles. Computers and Geotechnics, 42, 73-80.

[210] Papaioannou, I. and Straub, D. (2012). Reliability updating in geotechnical engineering including spatial variability of soil. Computers and Geotechnics, 42, 44-51.

6.3 Liquefaction

[211] Juang, C. H., Chen, C. J., Rosowsky, D. V. and Tang, W. H. (2000). CPT-based liquefaction analysis. Part 2. Reliability for design. Geotechnique, 50(5), 593-599.

[212] Huang, H. W., Zhang, J., and Zhang, L. M. (2012). Bayesian network for characterizing model uncertainty of liquefaction potential evaluation models. KSCE Journal of Civil Engineering, 16(5), 714-722.

[213] Wang, Y., Fu, C., and Huang, K. (2017). Probabilistic assessment of liquefiable soil thickness considering spatial variability and model and parameter uncertainties. Geotechnique, 67(3), 228-241.

6.4 Embankments

[214] Honjo, Y., Liu, W. T., and Soumitra, G. (1994). Inverse analysis of an embankment on soft clay by extended Bayesian method. International Journal of Numerical and Analytical Methods in Geomechanics, 18, 709-734.

[215] Wu, T. H., Zhou, S. Z. and Gale, S. M. (2007). Embankment on sludge: predicted and observed performances. Canadian Geotechnical Journal, 44, 545-563.

[216] Schweckendiek, T., Vrouwenvelder, A.C.W.M. and Calle, E.O.F. (2014). Updating piping reliability with field performance observations. Structural Safety, 47, 13-23

6.5 Slope Stability

[217] Luckman, P. G., Der Kiureghian, A., and Sitar, N. (1987). Use of stochastic stability analysis for Bayesian back calculation of pore pressures acting in a cut slope at failure. Proc., in 5th International Conf. on Application of Statistics and Probability in Soil and Struct. Engr., Vancouver, Canada.

[218] Reddi, L. N., and Wu, T. H. (1991). Probabilistic analysis of ground-water levels in hillside slopes. ASCE Journal of Geotechnical Engineering, 117(6), 872-890.

[219] Cheung, R. W. M. and Tang, W. H. (2005). Realistic assessment of slope reliability for effective landslide hazard management. Geotechnique, 55(1), 85 94.

[220] Zhang, J., Zhang, L. M., and Tang, W. H. (2009). Bayesian framework for characterizing geotechnical model uncertainty. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 135(7), 932--940.

[221] Zhang, L. L., Tang, W, H., and Zhang, L. M. (2009). Bayesian model calibration using geotechnical centrifuge tests. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 135(2): 291-299.

[222] Zhang, J., Tang, W. H., and Zhang, L. M. (2010). Efficient probabilistic back analysis of slope stability parameters. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 136(1), 99-109.

[223] Zhang, L. L., Zhang, J., Zhang, L. M., and Tang, W. H. (2010). Back analysis of slope failure with Markov chain Monte Carlo simulation. Computers and Geotechnics, 37(7-8), 905-912.

[224] Wang, Y., Cao, Z. J., and Au, S. K. (2010). Efficient Monte Carlo Simulation of parameter sensitivity in probabilistic slope stability analysis. Computers and Geotechnics, 37(7-8), 1015-1022.

[225] Samui, P., Lansivaara, T., and Kim, D. (2011). Utilization relevance vector machine for slope reliability analysis. Applied Soft Computing, 11(5), 4036-4040.

[226] Chiu, C. F., Yan, W. M. and Yuen, K. V. (2012). Reliability analysis of soil-water characteristics curve and its application to slope stability analysis. Engineering Geology, 135-136, 83-91.

[227] Zhang, J., Tang, W. H., Zhang, L. M. and Huang, H. W. (2012). Characterising geotechnical model uncertainty by hybrid Markov Chain Monte Carlo simulation. Computers and Geotechnics, 43(6), 26-36.

[228] Hasan, S. and Najjar, S. (2013). Probabilistic back analysis of failed slopes using Bayesian techniques. Geo-Congress 2013: Stability and Performance of Slopes and Embankments III (GSP 231), ASCE, Reston, VA, 1013-1022.

[229] Zhang, L. L., Zuo, Z. B., Ye, G. L., Jeng, D. S. and Wang, J. H. (2013). Probabilistic parameter estimation and predictive uncertainty based on field measurements for unsaturated soil slope. Computers and Geotechnics, 48, 72-81.

[230] Ranalli, M., Medina-Cetina, Z., Gottardi, G. and Nadim, F. (2014). Probabilistic calibration of a dynamic model for predicting rainfall-controlled landslides. ASCE Journal of Geotechnical and Geoenvironmental Engineering, 140(4), 04013039.

[231] Zhang, J., Huang, H. W., Juang, C. H., and Su, W. W. (2014). Geotechnical reliability analysis with limited data: consideration of model selection uncertainty. Engineering Geology, 181, 27-37.

[232] Zhang, L. L., Zheng, Y. F., Zhang, L. M., Li, X., and Wang, J. H. (2014). Probabilistic model calibration for soil slope under rainfall: effects of measurement duration and frequency in field monitoring. Geotechnique. 64(5), 365 378.

[233] Li, X. Y., Zhang, L. M, and Zhang, S. (2018). Efficient Bayesian networks for slope safety evaluation with large quantity monitoring information Geoscience Frontiers, 10.1016/j.gsf.2017.09.009.

6.6 Tunnels and Underground Openings

[234] Ledesma, A., Gens, A., and Alonso, E. E. (1996). Parameter and variance estimation in geotechnical back analysis using prior information. International Journal of Numerical and Analytical Methods in Geomechanics, 20, 114-141.

[235] Lee, M., Kim, D. H., and Lo, K. Y. (1997). A statistical approach on geotechnical parameter estimation for underground structures. In Proc. 9th International Conf. Computer Methods and Advances in Geomechanics, Wuhan, 775-780.

[236] Lee, I. M., and Kim, D. H. (1999). Parameter estimation using extended Bayesian method in tunneling. Computers and Geotechnics, 24(2), 109-124.

[237] Wang, L., Ravichandran, N., and Juang, C. H. (2012). Bayesian updating of KJHH model for prediction of maximum ground settlement in braced excavations in clays. Computers and Geotechnics, 44, 1-8.

[238] Spaková, O. and Straub, D. (2013). Dynamic Bayesian network for probabilistic modeling of tunnel excavation processes. Computer-Aided Civil and Infrastructure Engineering 28(1): 1-21

Dongming Zhang / TC309 / 29-04-2022

Reference List for Machine Learning and its Applications in Geotechnical Engineering - PART IV: PERFORMANCE COMPARISON OF MACHINE LEARNING ALGORITHMS USING THE SAME DATASET

1 Performance comparison of ML algorithms

1.1 Landslide

[1] Yao, X., Tham, L. G., and Dai, F. C. (2008). Landslide susceptibility mapping based on support vector machine: a case study on natural slopes of Hong Kong, China. Geomorphology, 101(4), 572-582. (One-class support vector machine, two-class support vector machine

[2] Marjanovic, M., Bajat, B., and Kovacevic, M. (2009). Landslide susceptibility assessment with machine learning al-

gorithms. In Intelligent Networking and Collaborative Systems, 2009. INCOS'09. International Conference on (pp. 273-278). IEEE. (Support vector machine with Gaussian kernel and k-Nearest Neighbor algorithms)

[3] Marjanovi, M., Kovaevi, M., Bajat, B., and Voenílek, V. (2011). Landslide susceptibility assessment using SVM machine learning algorithm. Engineering Geology, 123(3), 225-234. (Support vector machine, Decision tress, Logistic regression)

[4] Yilmaz, I. (2010). Comparison of landslide susceptibility mapping methodologies for Koyulhisar, Turkey: conditional probability, logistic regression, artificial neural networks, and support vector machine. Environmental Earth Sciences, 61(4), 821-836. (Conditional probability, logistic regression, artificial neural networks, and support vector machine)

[5] Tien Bui, D., Pradhan, B., Lofman, O., & Revhaug, I. (2012). Landslide susceptibility assessment in vietnam using support vector machines, decision tree, and Naive Bayes Models. Mathematical Problems in Engineering, 20(5), 705718. (Support vector machines, Decision tree, and Naive Bayes models)

[6] Pradhan, B. (2013). A comparative study on the predictive ability of the decision tree, support vector machine and neuro-fuzzy models in landslide susceptibility mapping using GIS. Computers and Geosciences, 51, 350-365. (Decision tree, Support vector marchine and adaptive neuro-fuzzy inference system (ANFIS))

[7] Goetz, J. N., A. Brenning, H. Petschko, and P. Leopold. (2015). Evaluating Machine Learning and Statistical Prediction Techniques for Landslide Susceptibility Modeling. Computers and Geosciences, 81: 111. (Generalized logistic regression, generalized additive models, weights of evidence, support vector machine, random forest classification, and bootstrap aggregated classification trees (bundling) with penalized discriminant analysis)

1.2 Liquefaction

[8] Samui, P., and Sitharam, T. G. (2011). Machine learning modelling for predicting soil liquefaction susceptibility. Natural Hazards and Earth System Sciences, 11(1), 1-9. (Artificial neural network, Support vector machine)

Dongming Zhang / TC309 / 29-04-2022

☙ ❧

International Society for Rock Mechanics and Rock Engineering

ISRM

News

https://www.isrm.net

ISRM launched a survey in English, Spanish and Chinese - deadline to complete it is 10 May 2022-04-01

ISRM launched a survey in English, Spanish and Chinese - deadline to complete it is 10 May

We would like to know more about our members and about those that have contact with us by visiting the website, subscribing to the Newsletter or following us on Twitter and LinkedIn. We would also like to know what you value most from our activities and what would you like us to offer to you.

For that purpose, the ISRM Board prepared a survey. To reach a larger number of people it can be completed in English, Spanish and Chinese. We strongly encourage you to take the 10 minutes required to complete it, because without your response we cannot provide to you the style of Society and the services that you want.

Please complete the survey by 10 May, when it will be closed.

Click here to start the survey.

Fourth ISRM Young Members' Seminar (YMS) on 28 April 2022-04-13

The ISRM Young Members' Seminar (YMS) Series is a new ISRM Young Members Group initiative. It consists of a series of virtual events, with the goal of providing a global platform for ISRM young members to share knowledge, experiences, and ideas. More details on the YMS are available on this page.

After three very successful editions, the fourth ISRM Young Members' Seminar will take place on 28 April at 7 A.M. GMT with two speakers, from Australia and New Zealand:

4th seminar - 28 April 2022

- Experimental analysis of burst type extreme rock failures and rock fracture under high-stress conditions by Selahattin Akdag (Australia).

- Coseismic rock slope failure mechanisms - insights from landslides triggered by the 2016 Mw 7.8 Kaiköura earthquake by Corine Singsein (New Zealand).

You can join using the Zoom link created for each Seminar and you can participate in the question and answers period. The Seminars will also be live-streamed to the ISRM YM's YouTube channel, where they will be stored. **Click here to download the flyer**.

Stay tuned for details on the 5th edition from the YMS organising committee.

Sevda Dehkhoda
Chair of the ISRM Young Members Committee

☙ ❧

Scooped by ITA-AITES #65, 12 April 2022

Tunnelling: Buried connections on the Grand Paris Express | France

Biden budget calls for $100 million for New York City tunnel project | United States of America

Argentina and Chile agree on three tunnel projects drilling the Andes

Tideway | Final connection tunnel complete on London super sewer | UK

Tunnel excavation work on 5km stretch in 2 weeks | India

The EU is building an $11billion tunnel connecting Scandinavia to the Mediterranean | Austria - Italy

India's first underwater metro tunnel in Kolkata to be made functional by 2023

Japan's largest underground bus terminal to be constructed at Tokyo Station

Central Interceptor micro-tunnel boring machine prepares for 722 m drive back | New Zealand

Construction of 9 km tunnel for Georgia's North-South road corridor underway | Georgia

Scooped by ITA-AITES #66, 26 April 2022

Submerged floating tunnel: principle, features, and challenges

Cross River Rail hits record milestone | Australia

TWAD Board completes tunnelling work in Pilloor III project | India

Montreal Blue Line Extension seeks TBM experience | Canada

Faroe tunnel investors "serious" about $3.4bn Channel Island link | UK

Managing the underground infrastructure legacy

New tunnelling industry group to promote low carbon linings

The underground labyrinth of the Paris Metro | France

Bulgaria plans to sign contract for Shipka tunnel construction in April

Architectural feats: Tunnels that spiral up, and were made by hand

Design and construction of a cavern in Downtown Los Angeles

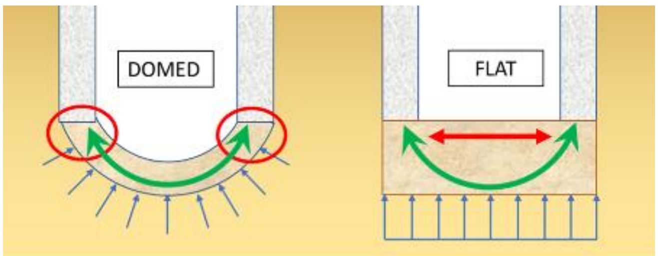
Carlos Herranz – Mott MacDonald

Los Angeles Metro is constructing a light rail corridor beneath Downtown Los Angeles—The Regional Connector Transit Corridor (RCTC). To provide operational flexibility, RCTC required a track crossover adjacent to one of the stations. Right of way constraints required the crossover be constructed at relatively shallow depth using Sequential Excavation Methods (SEM), resulting in what is believed to be the largest mined cross section in Los Angeles. Challenges faced for the SEM cavern design and construction included strict limits for tunnelling induced displacements in surrounding structures and high seismic design loads with 2,500 year return periods. This presentation describes the design approach of the SEM cavern, with an emphasis on the seismic analysis, as well as the actual conditions faced during construction.

Thursday 17th March 2022 The lecture will also be streamed live at https://youtu.be/Bdjs3VnpYDs

Flat or Domed? The Selection of Shaft Base Slab Geometry and a Medley of Design Considerations

Si Shen – TYPSA



In this lecture, Si will share some experience related to the structural design of underground concrete structures, often encountered in London area geology. The presentation will cover a seemingly insignificant but commonly seen issue in shaft design – the selection of geometry for the shaft base slab, flat and domed, each with its pros and cons.

This will expand into several related technical topics including:

- how cracking affects the design of underground concrete structures
- water resistance design of underground structures
- shrinkage, creep and early-age thermal behaviour of concrete.

The lecture will summarise how these characteristics of concrete influence the selection of base slab geometry.

This in-person lecture will also be streamed live at https://youtu.be/liFvEueNq24

Institution of Civil Engineers, London SW1P 3AA, Thursday 7 April 2022.

Osterberg Memorial Lecturer

DFI's 2022 Osterberg Memorial Lecture will take place on Thursday, June 16. Harry Poulos, Ph.D., D.Sc. Eng., senior consultant, Tetra Tech Coffey, and emeritus professor of civil engineering, University of Sydney, has been selected as this year's lecturer. The lecture is titled, **"Foundations for Tall Buildings – Design and Risk Reduction."**

Harry Poulos, Ph.D., D.Sc. Eng. Tetra Tech Coffey

Poulos joined the Department of Civil Engineering at Sydney University, his alma mater, in 1965, and was appointed a professor in 1982, a position he held until his retirement in 2001. In 1989, he joined Coffey Partners International and is currently as senior consultant with Tetra Tech Coffey. He is also an emeritus professor at the University of Sydney and an adjunct professor at Hong Kong University of Science and Technology. He is also the ombudsman for the DFI Journal.

Poulos has been involved in a large number of high-rise and infrastructure projects in Australia and overseas, including the Burj Khalifa and the Dubai Creek Tower in Dubai, and the 720 km Egnatia Odos motorway in Greece. In 2010, he was elected a Distinguished Member of the American Society of Civil Engineers (ASCE), and in 2014, he was inducted into the U.S. National Academy of Engineering. In 2017, he was awarded the Outstanding Leaders and Projects (OPAL) Award for lifetime achievement in design by ASCE, and in 2020 was awarded the Peter Nicol Russell Memorial Medal by Engineers Australia.

The annual Osterberg Memorial Lecture and Award was established in honor of Dr. Jorj O. Osterberg to recognize innovations in deep foundations construction related to engineering design, testing or education.

To view a listing of previous Osterberg Lecturers, **visit our website.**

Foundations For Tall Buildings – Design and Risk Reduction

The main issues to be considered in the design of foundations for tall buildings will be outlined, and procedures that can be adopted to address these issues will be discussed. Despite the evolution of modern techniques of ground investigation and foundation design, there have been cases in which problems have occurred and the performance of the supported building has been compromised. Some of the risk factors in foundation investigation, design and construction will be discussed, and measures to reduce such risks will be suggested. Examples of the successful application of the design and risk reduction procedures to two prominent tall buildings will be presented. A contemporary case in which a less successful outcome occurred will be discussed briefly. Possible reasons for this lack of success, and some of the lessons learned, will be outlined.

https://www.xcdsystem.com/dfi/program/2D2hmzD/index.cfm?pgid=1317#osterberg

Mediterranean Lecture 2022

June 15, 2022, Prof. Vassilis Marinos will deliver the fist Mediterranean Lecture "In-Flysch-Structure. Addressing the Challenge of Flysch in Major Infrastructure Projects". The event will be held in Naples at the faculty of Engineering. Further information can be found in our website: https://medgeocommunity.wixsite.com/website

The lecture will be followed by a lunch offered by the Università di Napoli.

The lecture will be spread also on-line.

The link: https://medgeocommunity.wixsite.com/website/about-3

Starting at 10.30 Rome time.

Award lectures from Charlotte Geo-Congress 2022

The following special lectures were given at the context of Geo-Congress 2022 (Charlotte, North Carolina | March 20-23 2022). All lectures can be found in the media gallery below.

Karl Terzaghi Lecture

This lectureship was established by the Soil Mechanics and & Foundations Division (present Geo-Institute) of the Society by the solicitation of gift from the many friends and admirers of Karl Terzaghi, Hon.M.ASCE. It was instituted by the Board of Direction on October 10, 1960.

2022 Winner

"Bio-mediated Geotechnics for Hazard Mitigation, Environmental Protection and Infrastructure Construction"

Edward Kavazanjian, Jr., PhD., P.E., D.GE, Dist. M. ASCE, NAE
Director, Center for Bio-mediated and Bio-inspired Geotechnics
Regents Professor and Ira A. Fulton Professor of Geotechnical Engineering Arizona State University

For significant contributions to earthquake engineering, the design of waste containment systems and in leading the emerging field of bio-geotechnical engineering.

Ralph B. Peck Award

This award was established in 1999 by the Geo-Institute of the Society in honor of Ralph B. Peck, Dist.M.ASCE. Funds to support this award were donated by the Geo-professional Business Association GBA (former ASFE).

2022 Winner

"Site Response analysis: Does it Work?"

Ellen Rathje, Ph.D., P.E., F.ASCE
Janet S. Cockrell Chair, The University of Texas Austin

For her advancements to seismic site response analysis through case histories, her development of case histories to inform regional seismic assessments and her leadership promoting the electronic publishing of case history data.

Bolton Seed Medal

This award was established by the Geotechnical Engineering Division (present Geo-Institute) of the Society in memory of Professor H. Bolton Seed, Hon.M.ASCE. It was officially instituted by action of the Board of Direction on October 23, 1993 and was funded by friends and colleagues of Professor Seed and the U.S National Society Endowment Fund.

2022 Winner

"Evaluating the effects of liquefaction"

Jonathan D. Bray, PhD., P.E., F.ASCE
Faculty Chair in Earthquake Engineering Excellence, UC Berkeley

For advancements in geotechnical earthquake engineering, including liquefaction ground motions, seismic site response, seismic slope stability, soil-structure-interaction (SSI) and surface fault rupture.

Carl L. Monismith Lecture

The ASCE Geo-Institute (G-I) has established a Lecture in recognition of Professor Carl L. Monismith's contribution to Pavement Engineering. Professor Monismith's teaching and research career in pavement technology, at the University of California Berkeley, spans more than 50 years. Throughout this period, he has mentored numerous graduate students who have disseminated advances in pavement technology around the world.

2021 Winner

"Unbound aggregate pavement layers-Dynamic loading behavior and its characterization"

Erol Tutumluer, Ph.D., M.ASCE
Abel Bliss Professor in Engineering
Paul F.Kent Endaved Faculty Scholar

For unique studying practical implications of geotechnical/pavement foundation issues in pavement design and performance and work on advanced and mechanistic based modeling of geo-mechanical and pavement systems.

Media

Geo-Congress 2022: Karl Terzaghi Lecture: Ed Kavazanjian

Geo-Congress 2022: H. Bolton Seed Lecture: Jonathan Bray

Geo-Congress 2022: Carl L. Monismith Lecture: Erol Tutumluer

Geo-Congress 2022: Ralph B. Peck Lecture: Ellen Rathje

Geo-Congress 2022: Karl Terzaghi Lecture: Ed Kavazanjian

Geo-Congress 2022: H. Bolton Seed Lecture: Jonathan Bray

Geo-Congress 2022: Carl L. Monismith Lecture: Erol Tutumluer

Geo-Congress 2022: Ralph B. Peck Lecture: Ellen Rathje

https://www.geoengineer.org/news/award-lectures-from-charlotte-geo-congress-2022

ASCE LIBRARY

March, 2022

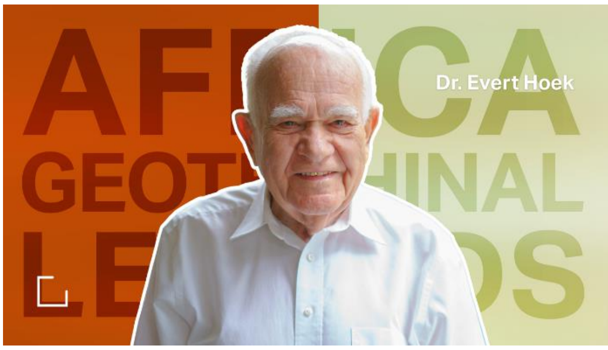
[Climate change creates new risks to dam safety](#)

Are the effects of climate change being considered in dam risk assessment? What happens during extreme rainfall or when water levels are higher than expected due to lower usage? Authors of a paper in the *Journal of Water Resources Planning and Management* looked at how risk assessments are used to ensure dam safety.

Watch Video

☙ ❧

rocscience



Design Challenges, Disasters, and Lessons in Rock Engineering

Dr. Hoek's video presentation and Q&A are now available.

The first seminar in the Africa Geotechnical Legends Series was a great success!

Dr. Hoek's presentation "**Design Challenges, Disasters, and Lessons in Rock Engineering**" can now be viewed on our YouTube channel.

Your participation during the session was highly appreciated. Dr. Hoek kindly answered all 95 questions asked during the session and formulated them into a document which can be accessed here.

Watch the Video

ΔΙΑΚΡΙΣΕΙΣ ΕΛΛΗΝΩΝ ΓΕΩΤΕΧΝΙΚΩΝ ΜΗΧΑΝΙΚΩΝ

Benefits of Unconventional Seismic Foundation Design
Διάλεξη Δρ. Γιώργου Γκαζέτα
Ομότιμου Καθηγητού ΕΜΠ

Μετά από πρόσκληση του Καθηγητού Νίκου Βλαχόπουλου στο GeoEngineering Centre του Queen's University – Royal Military College, Kingston, Ontario, Canada, ο Καθηγητής Γιώργος Γκαζέτας παρουσίασε, την Τετάρτη 6 Απριλίου 2022 την διάλεξη:

GeoEngineering Seminar Series
Sponsored by BGC Engineering
"Benefits of Unconventional Seismic Foundation Design"

Current seismic geotechnical practice has embraced concepts inspired by pseudo-static thinking and force-based methodologies. The result is often over-designed foundations that, in addition to being uneconomical and difficult to implement, might unexpectedly lead to poor technical performance of foundation–structure systems.
The lecture will address the benefits of drastically changing the established philosophy in seismic foundation design. Emphasis will be given to "foundation rocking and soil failure" of tall slender structures, the foundations of which we deliberately under-designed to ensure that during strong shaking substantially nonlinear and inelastic soil-foundation interaction takes place — uplifting of footing from the supporting soil, along with mobilisation of bearing-capacity failure mechanisms in the soil. Thanks to the kinematic nature of seismic shaking, allowing such unconventional response limits the accelerations transmitted up into the super-structure. Hence it reduces the inertia loading which "returns back" onto the foundation in the form of overturning moments and shear forces. Owing to its cyclic nature, seismic response generates a significant amount of damping in the soil, while exceedance of the ultimate capacity acts (only) momentarily and alternatingly. The two phenomena contribute towards decreased response intensity and acceptable levels of residual deformations (displacements and rotations). Deformations are further diminished by the beneficial contribution of gravity to re-centering of the foundation.
Physical experiments, analyses, and field observations, involving a variety of structural systems and foundations, will illustrate the technical advantages of such unconventional designs. Analysis of a historic seismic case history will further demonstrate the potential benefits (as well as the limitations) of this new paradigm in seismic soil–foundation–structure interaction.

The GeoEngineering Centre
Queen's UNIVERSITY
BGC

ΠΡΟΣΕΧΕΙΣ ΓΕΩΤΕΧΝΙΚΕΣ ΕΚΔΗΛΩΣΕΙΣ

Για τις παλαιότερες καταχωρήσεις περισσότερες πληροφορίες μπορούν να αναζητηθούν στα προηγούμενα τεύχη του «περιοδικού» και στις παρατιθέμενες ιστοσελίδες.

SYDNEY 7iYGEC 2021 7th International Young Geotechnical Engineers Conference A Geotechnical Discovery Down Under, 29 April - 1 May 2022, Sydney, Australia, http://icsmge2021.org/7iygec

SYDNEY ICSMGE 2021 20th International Conference on Soil Mechanics and Geotechnical Engineering, 1–5 May 2022, Sydney, Australia, www.icsgme2021.org

LARMS 2021 – IX Latin American Rock Mechanics Symposium Challenges in rock mechanics: towards a sustainable development of infrastructure, 15 – 18 May 2022, Asuncion, Paraguay, https://larms2021.com

3rd International Conference on Geotechnical Engineering - Iraq 2022, 17 to 19 May 2022, University of Baghdad, Iraq, https://ocs.uobaghdad.edu.iq/index.php/ICGEI/ticgei

Transport Geotechnics 2022, 19 May 2022, London, United Kingdom, https://transport.geplus.co.uk/getr/en/page/

2022 ICOLD 27th Congress - 90th Annual Meeting 27 May - 3 June 2022, Marseille, France, https://cigb-icold2022.fr/en

5th Meeting of EWG Dams and Earthquakes, Workshop on Ground motion selection approaches, May 31, 2022, Guillaume VEYLON, guillaume.veylon@inrae.fr

4th International Conference "Challenges in Geotechnical Engineering" CGE-2022, 1 to 3 June 2022, Kyiv, Ukraine www.cgeconf.com

The 17th Danube - European Conference on Geotechnical Engineering, 7-9 June, 2022, Bucharest, Romania, https://sites.google.com/view/17decgero

3rd European Conference on Earthquake Engineering and Seismology (3ECEES), 19-24 June 2022, Bucharest, Romania, https://3ecees.ro

PRF 2022 Progressive Failure of Brittle Rocks, June 20-24th, 2022, Flatrock, NC, USA, www.prf2022.org

3rd International Symposium on Geotechnical Engineering for the Preservation of Monuments and Historic Sites, 22-24 June 2022, Napoli, Italy, https://tc301-napoli.org

CPT'22 5th International Symposium on Cone Penetration Testing, 26-29 June 2022, Bologna, Italy, http://cpt22.org

Workshop on soil erosion for Europe – Emerging challenges, 27-29 June 2022 (WEBEX - Online) Landslides and soil erosion. Chair: Nikolaos Tavoularis ntavoularis@metal.ntua.gr

IS-Cambridge 2020 10th International Symposium on Geotechnical Aspects of Underground Construction in Soft Ground, 28 - 30 June 2022, Cambridge, United Kingdom, www.is-cambridge2020.eng.cam.ac.uk

5.ICNDSMGE – ZM 2020 5th International Conference on New Developments in Soil Mechanics and Geotechnical Engineering, June 30 to July 2, 2022, Nicosia, Cyprus, https://zm2020.neu.edu.tr

ICONHIC2022: THE STEP FORWARD - 3rd International Conference on Natural Hazards & Infrastructure, 5 – 7 July 2022, Athens, GREECE, https://iconhic.com/2021

RocDyn-4 4th International Conference on Rock Dynamics an ISRM Specialized Conference, 17-19 August 2022. Xuzhou, China, http://rocdyn.org

ISFOG 2020 4th International Symposium on Frontiers in Offshore Geotechnics, 28 – 31 August 2022, Austin, United States, www.isfog2020.org

16th International Conference of the International Association for Computer Methods and Advances in Geomechanics – IACMAG 30-08-2022 – 02-09-2022, Torino, Italy, www.iacmag2022.org

WTC 2022 World Tunnel Congress 2022 - Underground solutions for a world in change, 2-8 September 2022, Copenhagen, Denmark, www.wtc2021.dk

11th International Symposium on Field Monitoring in Geomechanics, September 4 - September 7, 2022, London, UK, https://isfmg2022.uk

7th European Geosynthetics Conference, 4 to 7 September, 2022, Warsaw, Poland, https://eurogeo7.org

3rd European Conference on Earthquake Engineering & Seismology, September 4 – September 9, 2022, Bucarest, Romania, https://3ecees.ro

Eurock 2022 Rock and Fracture Mechanics in Rock Engineering and Mining, 12÷15 September 2022, Helsinki, Finland, www.ril.fi/en/events/eurock-2022.html

IAEG XIV Congress 2022, Chengdu, China September 14-20, 2022, https://iaeg2022.org

28th European Young Geotechnical Engineers Conference and Geogames, 15 – 17 – 19 September 2022, Moscow, Russia, https://www.eygec28.com/?

International Workshop on Advances in Laboratory Testing of Liquefiable Soils, 17 September 2022, Kyrenia, North Cyprus, https://nce2022.ktimo.org

10th International Conference on Physical Modelling in Geotechnics (ICPMG 2022), September 19 to 23, 2022, KAIST, Daejeon, Korea, https://icpmg2022.org

11th International Conference on Stress Wave Theory and Design and Testing Methods for Deep Foundations, 20 - 23 September 2022, De Doelen, Rotterdam, The Netherlands, https://www.kivi.nl/afdelingen/geotechniek/stress-wave-conference-2022

10th Nordic Grouting Symposium, 4 - 6 October, 2022, Stockholm, Sweden, https://www.ngs2022.se/

Smart Geotechnics 2022, 6 October 2022, London UK, https://smartgeotechnics.geplus.co.uk/smartgeotechnics/en/page/home

IX Latin American Rock Mechanics Symposium - Challenges in rock mechanics: towards a sustainable development of infrastructure, an ISRM International Symposium, 16-19

October 2022, Asuncion, Paraguay, http://larms2022.com

5ο Πανελλήνιο Συνέδριο Αντισεισμικής Μηχανικής και Τεχνικής Σεισμολογίας, 20-22 Οκτωβρίου 2022, Αθήνα, https://5psamts.eltam.org

2022 GEOASIA7 - 7th Asian Regional Conference on International Geosynthetics Society, October 31 – November 4, 2022, Taipei, Taiwan, www.geoasia7.org

CouFrac 2022 - 3rd International Conference on Coupled Processes in Fractured Geological Media: Observation, Modeling, and Application, November 14-16, 2022, Berkeley, California, USA, https://coufrac2022.org

Piling & Ground Improvement Conference 2022, November 16-18, 2022, Sydney, Australia, https://events.americantradeshow.com/pilingconference2022

AUSROCK Conference 2022, 6th Australasian Ground Control in Mining Conference –an ISRM Regional Symposium, 29 November – 1 December 2022, Melbourne, Australia, www.ausimm.com/conferences-and-events/ausrock/

16th ICGE 2022 – 16th International Conference on Geotechnical Engineering, Lahore, Pakistan, 8-9 December, 2022, https://16icge.uet.edu.pk/

4th African Regional Conference on Geosynthetics – Geosynthetics in Sustainable Infrastructures and Mega Projects, 20-23 February 2023, Cairo, Egypt, www.geoafrica2023.org

ASIA 2023, 14 - 16 March 2023, Kuala Lumpur, Malaysia www.hydropower-dams.com/asia-2023

88th ICOLD Annual Meeting & Symposium on Sustainable Development of Dams and River Basins, April 2023, New Delhi, India, https://www.icold2020.org

UNSAT 2023 - 8th International Conference on Unsaturated Soils, 2-5 May 2023, Milos island, Greece, www.unsat2023.org

World Tunnel Congress 2023 Expanding Underground Knowledge & Passion to Make a Positive Impact on the World, 12 - 18 May 2023, Athens, Greece, https://wtc2023.gr

cs ho

NROCK2022
The IV Nordic Symposium on Rock Mechanics and Rock Engineering
24 – 25 May 2023, Reykjavic, Iceland
www.nrock2023.com

The Icelandic Geotechnical Society and The Icelandic Tunnelling Society are pleased to welcome you to the Nordic Rock Meeting - the IV Nordic Symposium on Rock Mechanics and Rock Engineering in Reykjavik, Iceland 24 - 26 of May 2023.

This symposium gathers Nordic rock mechanics and engineering geology experts to discuss the current state of research, infrastructure, rock caverns, tunnelling, mining, use of underground space for energy recovery and storage, and case histories. Use of underground space for various purposes is a natural choice in Nordic countries and it has made the understanding of rock mechanics and rock engineering vital. Be welcome and meet your colleagues at the Nordic Rock Meeting in Reykjavik, Iceland.

The Nordic Rock Meeting was establised by the Norwegian Rock Mechanic Group and the first meeting was held in Norway 2010, followed by meetings in Sweden and Finland and the next meeting, the 4th, is planned in Reykjavik Iceland in 2023.

The Nordic Rock Meetings
2010 Kongsberg - Norway
2013 Göteborg - Sweden
2017 Helsinki - Finland
2023 Reykjavik - Iceland

The aim of the symposium is to strengthen the relationships between practicing engineers, researchers and scientists within the fields of Rock Mechanics and Engineering Geology with special emphasis on, but not limited to, the Nordic region.

This symposium is a platform to gather experts within the area of rock mechanics with the topical themes related to current state of research, infrastructure, rock caverns, tunnelling, mining, use of underground space for different type of storage and case histories.

All are invited to share their experience and knowledge with their Nordic colleagues by delegation in the technical program as well the social one.

Address

Icelandic Geotechnical Society Engjateigur 9 105 Reykjavík ICELAND
Contact Person Name Thorbjorg Thrainsdottir
Email jardtaeknifelagid@gmail.com

cs ho

3rd JTC1 Workshop on "Impact of global changes on landslide risk", 7 – 10 June 2023, Oslo, Norway, https://jtc1-2023.com

9th International Congress on Environmental Geotechnics Highlighting the role of Environmental Geotechnics in Addressing Global Grand Challenges, 25-28 June 2023, Chania, Crete island, Greece, www.iceg2022.org

17ARC 17th Asian Regional Geotechnical Engineering Conference, 14-18 August 2023, Nur-Sultan, Kazakhstan, https://17arc.org

IS-PORTO 2023 8th International Symposium on Deformation Characteristics of Geomaterials, 3rd - 6th September 2023, Porto, Portugal, www.fe.up.pt/is-porto2023

Innovative Geotechnologies for Energy Transition, 12-14 September 2023, London, UK, www.osig2023.com

SAHC 2023 13th International Conference on Structural Analysis of Historical Constructions "Heritage conservation across boundaries", 12-15 September 2023, Kyoto, Japan, https://sahc2023.org/

XII ICG - 12th International Conference on Geosynthetics, September 17 – 21, 2023, Rome, Italy, www.12icg-roma.org

2023 15th ISRM Congress, International Congress in Rock Mechanics Challenges in Rock Mechanics and Rock Engineering, 9÷14 October 2023, Salzburg, Austria, https://www.isrm2023.info/en/

6th World Landslide Forum "Landslides Science for sustanaible development", 14 to 17 November 2023, Florence, Italy, https://wlf6.org

World Tunnel Congress 2024
Shenzhen, China

China is the official host of the ITA-AITES World Tunnel Congress 2024 and 50th General Assembly.

The General Assembly which took place on June 30th by video-conference, has confirmed the candidacy of Shenzhen to organise the WTC 2024.

XVIII European Conference on Soil Mechanics and Geotechnical Engineering
25-30 August 2024, Lisbon, Portugal

Organiser: SPG
Contact person: SPG
Address: Av. BRASIL, 101
Email: spg@lnec.pt
Website: http://www.spgeotecnia.pt

ΕΝΔΙΑΦΕΡΟΝΤΑ ΓΕΩΤΕΧΝΙΚΑ ΝΕΑ

Mount Bolu: an interesting case study of a tunnel portal landslide in Turkey

On 2 April 2022 heavy rainfall triggered an economically significant landslide in at Mount Bolu in Turkey. The landslide occurred after a spell of rainfall that in places has fallen onto snow. This is a recipe for landslides in upland areas.

The Mount Bolu Tunnel landslide is interesting though. It has blocked four lanes of the D-100 road, a critical east-west connection across the north of Turkey. This is an image of the landslide:-

The aftermath of the landslide at Mount Bolu in Turkey.

This is an alternative view that shows the landslide source more clearly, as well as some of the debris blocking the carriageway:-

The landslide at Mount Bolu in Turkey.

The site of the tunnel is at 40.7578, 31.4504. It is clearly visible on Google Earth. The tunnel was completed in 2007.

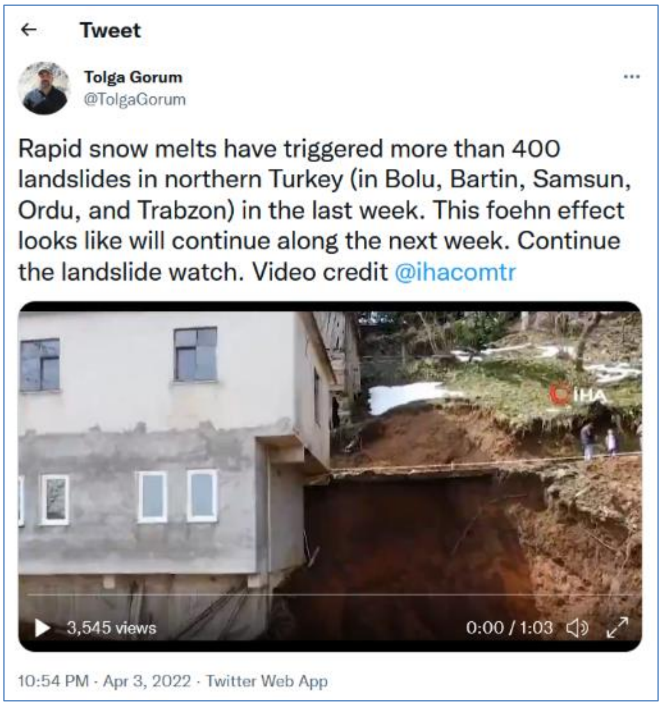
There are some very interesting images online of the site of this landslide prior to the 2 April 2022 landslide. This image for example shows the tunnel portals and the slope above:-

The archive of Google Earth imagery does not seem to indicate that further works have been undertaken to stabilise this slope, although of course satellite/aerial imagery has limitations. But on first inspection this is an ugly slope to be located above a tunnel portal on such an important highway, especially in a region that is seismically active.

Archive image of the site of the Mount Bolu landslide, showing the pre-existing landslide scarps.

The debris has taken 44 hours to clear, but the road has now reopened. The images suggest that further works will be needed on the slopes at this site, both in the scar of the 2 April 2022 landslide and on the slope to the left of it (as seen in the images), which appears to be another potential landslide site.

Northern Turkey has been suffering from a wave of landslides in recent days:-



https://twitter.com/TolgaGorum/status/1510707374780256256?ref_src=twsrc%5Etfw%7Ctwcamp%5Etweetembed%7Ctwterm%5E1510707374780256256%7Ctwgr%5E%7Ctwcon%5Es1_&ref_url=https%3A%2F%2Fblogs.agu.org%2Flandslideblog%2F2022%2F04%2F05%2Fmount-bolu-1%2F

(Dave Petley / THE LANDSLIDE BLOG, 5 April 2022, https://blogs.agu.org/landslideblog/2022/04/05/mount-bolu-1)

Dam failures caught on camera | Dam Failure Compilation

9 Structural failures in dams, hydroelectric plants and spillways from different parts of the world

https://www.youtube.com/watch?v=02vJC3_KLWI

15 Massive Dam Failures

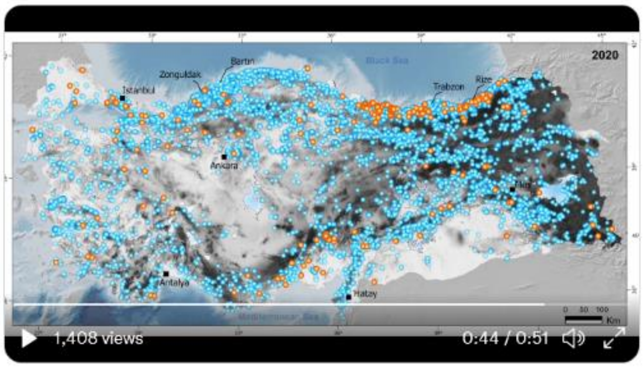
Human engineering isn't perfect and sometimes mistakes can happen. Today we're going to take a look at 15 of the largest dam failures in human history.

https://www.youtube.com/watch?v=gSMXem81Vk4

Turkish Multiple Landslide Event Archive Inventory

We have completed the Turkish Multiple Landslide Event Archive Inventory for the last three decades. This inventory, prepared by @itu1773, @AYBE, and @itugeohazard

Research Group, will contribute to a comprehensive understanding of the landslide hazard in Turkey.



Tolga Gorum, @TolgaGorum, Apr 6, 2022·Twitter Web App

Kithira island (in Southwest Greece)

This island is very close to the border of the Eurasian and African tectonic plates, and as a consequence, many geological events take place throughout time (e.g. earthquakes, landslides, subsidences). A rockfall at Galani spring near the village of Agia Pelagia (Eastern side of Kithira Island, Greece) has been taken by a UAV in February 2019.

The place is located in the joint of two faults and is surrounded by limestones and schists. A geotechnical investigation is taking place to find the appropriate mitigation measures.

Nikolaos Tavoularis
Dr. Engineering Geology
NTUA, Greece

IAEG Connector E-News, 13.04.2022

ΕΝΔΙΑΦΕΡΟΝΤΑ - ΣΕΙΣΜΟΙ & ΑΝΤΙΣΕΙΣΜΙΚΗ ΜΗΧΑΝΙΚΗ

Scientists find evidence for biggest earthquake in human history

The quake was so ruinous, humans fled the area for 1,000 years.

The earthquake sent waves as high as 66 feet 5000 miles across the Pacific Ocean. (Image credit: Shutterstock)

Archaeologists have found evidence of the largest known earthquake in human history — a terrifying magnitude-9.5 megaquake that caused a 5,000-mile-long (8,000 kilometers) tsunami and prompted human populations to abandon nearby coastlines for 1,000 years, a new study finds.

The earthquake struck about 3,800 years ago in what is now northern Chile when a tectonic plate rupture lifted the region's coastline. The subsequent tsunami was so powerful, it created waves as high as 66 feet (20 meters) and traveled all the way to New Zealand, where it hurled car-size boulders hundreds of miles inland, the researchers found.

Until now, the largest earthquake ever recorded was the 1960 Valdivia earthquake, which hit southern Chile with a magnitude between 9.4 and 9.6, killing up to 6,000 people and sending tsunamis barreling across the Pacific Ocean. The rupture that caused the Valdivia earthquake was enormous, extending as far as 500 miles (800 km) in length. But, as scientists detail in research published April 6 in the journal Science Advances, the newly discovered ancient megaquake was even bigger, coming from a rupture roughly 620 miles (1,000 km) long.

"It had been thought that there could not be an event of that size in the north of the country simply because you could not get a long enough rupture," study co-author James Goff, a geologist at the University of Southampton in England, said in a statement.

Like the Valdivia earthquake, the ancient quake was a megathrust earthquake, the most powerful type of earthquake in the world. These earthquakes occur when one of Earth's tectonic plates gets forced, or subducted, underneath another. The two plates eventually get locked into place by friction, but the forces that caused the plates to collide continue to build. Eventually, so much strain gathers that the point of contact between the plates rips apart, creating a gigantic rupture and releasing energy in the form of devastating seismic waves.

Evidence for the giant quake was found in marine and coastal items — such as littoral deposits (boulders, pebbles and sand native to coastal regions) and marine rocks, shells and sea life — that the researchers discovered displaced far inland in Chile's Atacama Desert.

"We found evidence of marine sediments and a lot of beasties that would have been living quietly in the sea before being thrown inland," Goff said in the statement. "And we found all these very high up and a long way inland, so it could not have been a storm that put them there."

To get a better sense of what brought these deposits so far from the sea, the researchers used radiocarbon dating. This method involves measuring the quantities of carbon 14, a radioactive carbon isotope, found inside a material to determine its age. As carbon 14 is everywhere on Earth, deposits easily absorb it while they form. The half-life of carbon 14, or the time it takes for half of it to radioactively decay, is 5,730 years, making it ideal for scientists who want to peer back into the last 50,000 years of history by checking how much undecayed carbon 14 a material has.

After dating 17 deposits across seven separate dig sites over 370 miles (600 km) of Chile's northern coast, the researchers found that the ages of the out-of-place coastal material suggested that it had been washed inland some 3,800 years ago.

Further evidence also came in the form of ancient stone structures that the archaeologists excavated. These stone walls, built by humans, were found lying beneath the tsunami's deposits, and some were lying backward, pointing toward the sea, suggesting that they had been toppled by the strong currents of the tsunami's backwash.

"The local population there were left with nothing," Goff said. "Our archaeological work found that a huge social upheaval followed as communities moved inland beyond the reach of tsunamis. It was over 1,000 years before people returned to live at the coast again, which is an amazing length of time given that they relied on the sea for food."

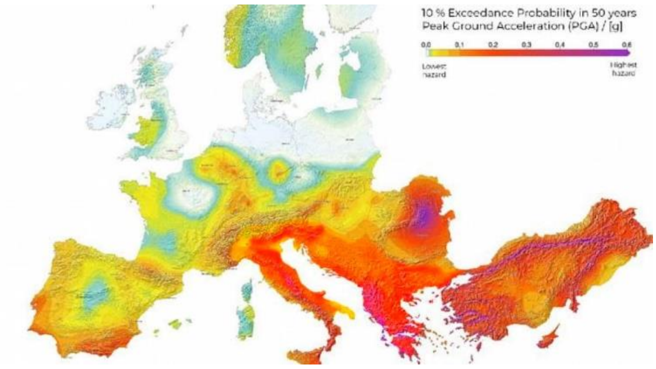
As this is the oldest known discovery in the Southern Hemisphere of an earthquake and tsunami devastating human lives, the researchers are excited to probe the region further. They think their research could better inform us of the potential dangers of future megathrust quakes.

"While this had a major impact on people in Chile, the South Pacific islands were uninhabited when they took a pummeling from the tsunami 3,800 years ago," Goff said. "But they are all well-populated now, and many are popular tourist destinations. So when such an event occurs next time, the consequences could be catastrophic unless we learn from these findings."

(Ben Turner / LIVE SCIENCE, 19 April 2022, https://www.livescience.com/biggest-earthquake-found-chile)

First Europe earthquake risk model: Balkan countries most dangerous

During the 20th century, earthquakes in Europe accounted for more than 200,000 deaths and over 250 billion euros in losses.



World   Europe earthquake map

Comprehensive earthquake hazard and risk assessments are crucial to reducing the effects of catastrophic earthquakes because earthquakes cannot be prevented nor precisely predicted.

An international team of European seismologists, geologists, and engineers, with leading support of members from the Swiss Seismological Service and the Group of Seismology and Geodynamics at ETH Zurich has; therefore, revised the earthquake hazard model that has existed since 2013 and created a first earthquake risk model for the whole of Europe.

The 2020 European Seismic Hazard and Risk Models offer comparable information on the spatial distribution of expected levels of ground shaking due to earthquakes, their frequency as well as their potential impact on the built environment and on people's sense of wellbeing.

The newly released update of the earthquake hazard model and the first earthquake risk model for Europe are the basis for establishing mitigation measures and making communities more resilient. They significantly improve the understanding of where strong shaking is most likely to occur and the potential effects of future earthquakes in Europe.

To this aim, all underlying datasets have been updated and harmonised – a complex undertaking given the vast amount of data and highly diverse tectonic settings in Europe. Such an approach is crucial to establish effective transnational disaster mitigation strategies that support the definition of insurance policies or up-to-date building codes at a European level and at national levels.

Open access is provided to both, the European Seismic Hazard and Risk Models, including various initial components such as input datasets.

Earthquake hazard describes potential ground shaking due to future earthquakes and is based on knowledge about past earthquakes, geology, tectonics, and local site conditions at any given location across Europe.

The advanced datasets incorporated into the new version of the model have led to a more comprehensive assessment of the earthquake hazard across Europe. In consequence, ground shaking estimates have been adjusted, resulting in lower estimates in most parts of Europe, compared to the 2013 model, and in the case of Switzerland closer to the national model.

With the exception of some regions in western Turkey, Greece, Albania, Romania, southern Spain, and southern Portugal where higher ground shaking estimates are observed.

The updated model also confirms that Turkey, Greece, Albania, Italy, and Romania are the countries with the highest earthquake hazard in Europe, followed by the other Balkan countries. But even in regions with low or moderate ground shaking estimates, damaging earthquakes can occur at any time.

Furthermore, specific hazard maps from Europe's updated earthquake hazard model will serve for the first time as an informative annex for the second generation of the Eurocode 8 (European standards related to construction). Eurocode 8 standards are an important reference to which national models may refer.

Such models, when available, provide authoritative information to inform national local decisions related to developing seismic design codes and risk mitigation strategies. Integrating earthquake hazard models in specific seismic design codes helps ensure that buildings respond appropriately to earthquakes.

These efforts thus contribute to better protect European citizens from earthquakes.

Earthquake risk describes the estimated economic and humanitarian consequences of potential earthquakes. In order to determine the earthquake risk, information on local soil conditions, the density of buildings and people (exposure), the vulnerability of the built environment, and robust earthquake hazard assessments are needed. According to the 2020 European Seismic Risk Model (ESRM20), buildings constructed before the 1980s, urban areas, and high earthquake hazard estimates mainly drive the earthquake risk.

Although most European countries have recent design codes and standards that ensure adequate protection from earthquakes, many older unreinforced or insufficiently reinforced buildings still exist, posing a high risk for their inhabitants.

The highest earthquake risk accumulates in urban areas, such as the cities of Istanbul and Izmir in Turkey, Catania, and Naples in Italy, Bucharest in Romania, and Athens in Greece, many of which have a history of damaging earthquakes.

In fact, these four countries alone experience almost 80% of the modelled average annual economic loss of 7 billion Euros due to earthquakes in Europe.

However, also cities like Zagreb (Croatia), Tirana (Albania), Sofia (Bulgaria), Lisbon (Portugal), Brussels (Belgium), and Basel (Switzerland) have an above-average level of earthquake risk compared to less exposed cities, such as Berlin (Germany), London (UK), or Paris (France).

A core team of researchers from different institutions across Europe, including the leading support of members from ETH Zurich, worked collaboratively to develop the first openly available Seismic Risk Model for Europe and to update Europe's Seismic Hazard Model.

They have been part of an effort that started more than 30 years ago and involved thousands of people from all over Europe. These efforts have been funded by several European projects and supported by national groups over all these years.

Researchers from the Swiss Seismological Service (SED) and the Group of Seismology and Geodynamics at ETH Zurich led many of these projects.

The SED is also home to EFEHR (European Facilities for Earthquake Hazard and Risk).

EFEHR is a non-profit network dedicated to the development and updating of earthquake hazard and risk models in the European-Mediterranean region.

ETH Zurich thus holds a central hub function for data collection and processing, open access to earthquake hazard and risk models including all basic data sets, and knowledge exchange.

(Christian Fernsby / POST ONLINE MEDIA MAGAZINE, April 29, 2022, https://www.poandpo.com/in-the-mean-time/first-europe-earthquake-risk-model-balkan-countries-most-dangerous)

Ποιο στοιχείο «δείχνει» ενδεχόμενο σεισμό και τι συμβαίνει στον Κορινθιακό Κόλπο - Ειδικοί εξηγούν

Τι δείχνει έρευνα Ελλήνων επιστημόνων

Αντικείμενο έρευνας επιστημόνων από την Ελλάδα και τις ΗΠΑ αποτελεί η πολυτελής μελέτη των μεταβολών της εδαφικής συγκέντρωσης του ραδονίου ως προδρόμου φαινομένου των σεισμών, με τους ερευνητές να εστιάζουν στον Κορινθιακό Κόλπο.

Ειδικότερα στην περίπτωση του Ανατολικού Κορινθιακού Κόλπου, διαπιστώθηκε σταδιακή αύξηση του ραδονίου κατά την περίοδο πριν από τους σεισμούς, απότομη πτώση λίγες ημέρες πριν και στη συνέχεια σταθεροποίηση σε ένα νέο επίπεδο μέχρι να αρχίσει και πάλι η σταθερή άνοδος.

Οι ερευνητές, με επικεφαλής τον δρα Β.Κ. Καραστάθη, αναπληρωτή διευθυντή του Γεωδυναμικού Ινστιτούτου του Εθνικού Αστεροσκοπείου Αθηνών (ΕΑΑ), έκαναν στη σχετική δημοσίευση στο περιοδικό "Nature Reports". Στην έρευνα συμμετείχαν επίσης οι Άκης Τσελέντης, Γιώργος Ελευθερίου και Ευάγγελος Μουζακιώτης του Γεωδυναμικού Ινστιτούτου του ΕΑΑ, οι γεωφυσικοί Μηνάς Καφάτος και Ντίμιταρ Ουζούνοφ από το Κολλέγιο Επιστήμης και Τεχνολογίας Schmid του Πανεπιστημίου Τσάπμαν στην Καλιφόρνια, καθώς επίσης ο Κανάρης Τσίγκανος, ομότιμος καθηγητής του Τμήματος Φυ-σικής του ΕΚΠΑ.

Το Εθνικό Αστεροσκοπείο Αθηνών διατηρεί την τελευταία πενταετία δίκτυο ραδιομετρικών σταθμών ακτινοβολίας-γ, οι οποίοι είναι τοποθετημένοι σε βάθος στο έδαφος, σε διάφορες θέσεις της Δυτικής Ελλάδας, των Ιονίων νήσων, του Ανατολικού Κορινθιακού κόλπου και της Κρήτης. Η νέα επιστημονική δημοσίευση περιλαμβάνει κυρίως τα αποτελέσματα που αφορούν στη σεισμική ζώνη του Ανατολικού Κορινθιακού κόλπου.

Αν και οι μεταβολές του ραδονίου έχουν προταθεί εδώ και δεκαετίες ως πρόδρομο φαινόμενο σεισμών, δεν έχει εξηγηθεί επαρκώς ο μηχανισμός που διέπει το φαινόμενο, αλλά και το γεγονός ότι κάποιες περιοχές είναι πιο ευαίσθητες σε τέτοιες μεταβολές από τις γειτονικές τους.

Οι ερευνητές προτείνουν ότι οι μεταβολές της εδαφικής συγκέντρωσης ραδονίου ακολουθούν ένα συγκεκριμένο χαρακτηριστικό μοτίβο, που ακολουθεί τη μεταβολή της συγκέντρωσης των τεκτονικών τάσεων σε μία περιοχή. Η μελέτη εξηγεί σε μεγάλο βαθμό, μέσω ενός προτεινόμενου μοντέλου βαθιάς υδρογεωλογίας, την προνομιακή καταγραφή σε γεωθερμικές θέσεις, αλλά και τη συσχέτιση με αποτελέσματα εργαστηριακών πειραμάτων.

Αν και από τα πρώτα στάδια της έρευνας διαπιστώθηκαν σαφείς ενδείξεις για την ύπαρξη ενός χαρακτηριστικού μοτίβου στην κύμανση του εδαφικού ραδονίου πριν τους σεισμούς, οι ερευνητές προτίμησαν να επιβεβαιώσουν πολλαπλώς την ύπαρξη του φαινομένου, έτσι ώστε να υπάρχει υψηλή αξιοπιστία στις παρατηρήσεις τους για ένα τόσο σημαντικό ερευνητικό θέμα, που αφορά άμεσα και την κοινωνία. Οι γεωφυσικές παρατηρήσεις αποδόθηκαν με ασφάλεια στις τεκτονικές διεργασίες, αφού εξετάστηκε ενδελεχώς και η οποιαδήποτε πιθανή επιρροή των ατμοσφαιρικών παραμέτρων στις μετρήσεις.

(The LiFO team / 3 Απριλίου 2022, https://www.lifo.gr/now/tech-science/poio-stoiheio-deihnei-endehomeno-seismo-kai-ti-symbainei-ston-korinthiako-kolpo)

Observations on the stress related variations of soil radon concentration in the Gulf of Corinth, Greece

Vassilios K. Karastathis, George Eleftheriou, Menas Kafatos, Kanaris Tsinganos, G-Akis Tselentis, Evangelos Mouzakiotis & Dimitar Ouzounov

Abstract

Our observations indicate a characteristic pattern in the long-term variation of soil radon concentrations, which seems to be consistent with the expected variation of regional stress in relation to seismicity. However, it seems that the major changes in radon level begin before the rock rapture, i.e. before the earthquake occurs. These conclusions have emerged after long-term observations with continuous and thorough real-time gamma-radiation monitoring in the seismically active area of the Gulf of Corinth, Greece. The recordings acquired close to a hot spring were of very high quality, implying that the deep hydraulic flow can possibly play a key role in the pre-earthquake variation of radon level. We were able to observe outstanding examples of radon level variations before significant seismic events in the Gulf of Corinth that cannot be attributed to other external factors such as atmospheric phenomena.

Introduction

The human attempt to forecast earthquakes through the observation of precursory phenomena began from the early historic times. Apollonius Paradoxographus (Historiae mirabiles 5), Cicero (On Divination, Book I, 50) and Diogenes Laërtius

(I. 116) report the case of Pherecydes, the famous teacher of Pythagoras, who successfully predicted that an earthquake was to occur at three days, by examining water from a well. Besides that, Cicero mentions that Anaximander, a student of the Greek philosopher Thales of Miletus, in 550 BC, warned the inhabitants of Sparta, of an upcoming strong earthquake, and since they stayed all night outside their homes, they saw their city being completely destroyed (Cicero, On Divination, Book I, 50). Pausanias also extensively describes the existence of precursor phenomena before earthquakes when he reports the strong event of Helice in 373 BC (Pausania, Achaika, 24–7).

As huge disasters and losses in human lives often occur due to earthquakes, even in economically developed countries, human societies will persistently strive to succeed in successfully forecasting earthquakes. Although these efforts have not reached their ultimate target so far in achieving systematic, reliable and accurate short-term prediction, they are continued and intensified in recent years. Nowadays, contemporary technology is providing new means to explore and study possible earthquake precursors with new-found vigor.

The general principle and philosophy of the effort for short-term earthquake prediction is based on the consideration that such a large-scale phenomenon involves a considerable time and space of preparation depending on its magnitude[1,2]. Within this process and based on the dynamics of the plate tectonics, the potential cause for the creation and occurrence of the "precursor phenomena" is the significant change in stress, developed before the rupture[3]. Since an earthquake is proven to be related with various other physical fluctuations (such as gas emission, geodetic, electromagnetic etc.), it is also clear that it is not only limited to its "mechanical" or "dynamic" nature but also causes a number of other phenomena, several of which are well documented with numerous measurements[4,5,6]. A concise and thorough presentation of the earthquake precursors has been compiled by Cicerone et al.[7] Of all, perhaps, the precursory phenomena that have been proposed, the variations in the noble radioactive gas Radon (222Rn) is what has undoubtedly been the most-discussed in the past, with extensive literature and a wealth of data. Despite the fact that first evidence came quite early, and rather unintentionally, when just after the Uzbekistan's Tashkent earthquake in 1966, Soviet scientists correlated the radon changes with the associated seismic events sequence[8] and in spite of intensive research efforts in the decades that followed, this pre-earthquake process has not yet been exploited as an actual earthquake forecasting tool.

In related literature, there are many publications that claim to describe some connection between radon variations and upcoming earthquake events; however, such an association has been well documented only in a limited number of cases. Experimental research has shown a particularly important and direct dependence of radon changes on external factors such as variations of pressure, wind, temperature, etc[9,10]. Since atmospheric variations occur on both, a daily and a seasonal basis reaching occasionally extreme levels, monitoring of all atmospheric parameters and a long-term correlation with the soil radon concentration is necessary. The problem of assessing an anomaly and attributing it to an earthquake becomes even more difficult, if we take into consideration the fact that the choice of the occurrence time of the precursor phenomenon is quite arbitrary, without any specific rule. If, in simple terms, there is an anomaly in radon concentration, before weeks or just a few hours before an actual earthquake, scientists could possibly interpret it as a precursor of this event. It is, therefore, obvious that a long-term time series of radon concentration measurements is required, in different locations, in order to clarify the correlation between radon variation and other external factors before finally interpreting correctly an actual signal. Systematic studies have been carried out in the past with extended networks in Japan, China and other countries[11]. Observations are often reported for earthquakes very distant from the epicenter, where no significant changes of stress are expected[2,12] and also gas transfer to large distances could not be realistic due to the short half-life of radon (3.82d)[13]. Additionally, concurrent radon recordings appear to have strong local features i.e. two relatively neighboring radon stations may considerably differ in measurements[14] as is the case with most preseismic signals that exhibit "response heterogeneity"[15].

According to the theory of the dilatancy-diffusion model [3,16,17], variations in the stress field and growth of cracks in rocks are proposed as the main reason of changes in radon concentration. Giardini et al.[18] have also been led to similar findings for other gasses in the earth's crust. Experimental data obtained under low and high level filling of the Roselend reservoir in the French Alps support this hypothesis quite well [19]. Besides, data from the Izu-Oshima-kinkai earthquake (M7.0) on January 14, 1978[11] showed that the measured radon changes were consistent with the deformation measured by strainmeters and also with the temperature and level variations of the aquifers. Similar work has been done for radon measurements in the atmosphere in the case of the Kobe earthquake, in 1995[20,21,22,23]. Although the relation between stress and radon concentration in the reservoir experiments appears to be possible, the values of the induced stresses were small and not much larger than 1 bar/10 m of water depth. Based on this, Roeloffs[24] proposed a nonlinear behavior of rock mass at low stresses that is mainly dominated by deformation of fluid-filled void space, including cracks and faults.

Rikitake and Hamada[2] proposed that no precursor has been observed with crustal strain under the threshold value of 10^{-9}. However, this limit is by far smaller than the respective one of the regular geodetic monitoring of precursory land deformation which is not better than 10^{-7}. The extent of this zone of land deformation prior to the earthquake is expected to be very small[25]. It is clear that even if the most sensitive instruments were used, such as high-resolution strainmeters, in order to monitor a possible strain due to the aseismic fault slip near the earthquakes nucleation point, this would have to be performed within a small radius of just a few kilometers from the epicenter[24].

From the research work of Kawada et al.[20] it was shown that the increase in radon before strong earthquakes can be related to crustal deformation, cumulative Benioff strain and porosity change which is a critical parameter for radon migration.

The relation between stress and radon variation has been investigated also on laboratory scales[26,27,28]. Holub and Brady[27] showed that a uniaxial compression on a granitic rock sample proportionally increases the exhalation of radon-222 that comes out from the pore space before any cracks are appeared and off course before the rupture of the rock sample take place. In their experiment a decrease in emanation was measured during the initial loading that was attributed to the closure of the existing cracks. The pressure that led the sample to failure increased the radon emanation up to 120% since with half pressure the radon increase reached the 50%. It is worth noting that after the failure, a level 5% has remained higher than what it was in the pre-experiment state. The experiment finally produced a characteristic curve of radon variation with respect to stress.

The question remains nevertheless, weather there is any similarity between soil radon measurements and those measured in the laboratory. Jiang and Li[29] also worked on granite samples under uniaxial stress and found that the radon emanation began to increase before failure. Furthermore a major increase in radon emanation occurred during the rupture. However, their experiments with limestone and basalt samples with low uranium (U_3O_8) and thorium (ThO_2) concentrations under similar loading conditions didn't produce similar results. King and Luo[28] showed a possible correlation between radon emanation and stress by conducting experiments on concrete, which is very porous in comparison to granites and could better resemble materials encountered in tectonic structures and faults and suggested that the increase can be mostly attributed to the creation and development of axial dilatant microcracks which tend to increase the surface area for gas emanation and permeability. The development of axial dilatant microcracks has been proposed as pre-earthquake process by Thomas[30].

In this article we present examples of clear changes in soil radon concentration before earthquakes. We further investigate whether these recorded anomalies follow a specific pattern, which may be related to changes in stress. We also examine whether these anomalies are recorded simultaneously with similar characteristics in neighboring stations. Our ultimate goal is to test the validity of a possible direct connection of the radon anomaly with stress changes.

In order to monitor the variation of soil radon concentration before strong earthquakes, we installed 6 recording stations at high seismicity areas such as the eastern part of the Gulf of Corinth and also at the Hellenic trench in Western Greece (Fig. 1). The active tectonic structures of the Greek region constitute an ideal natural laboratory for the research of earthquake precursors. The investigation of the physical processes that determine the occurrence of such phenomena contributes crucially to a deep understanding of the geodynamic regime of these active regions. This understanding continuously improves the practices for a proper seismic hazard assessment of areas in direct proximity to big urban centers and highly important energy and industry infrastructures. The Gulf of Corinth and its broader area has much suffered in the past by many catastrophic and lethal earthquakes. Knowledge of the precursor phenomena can contribute decisively to earthquake forecasting.

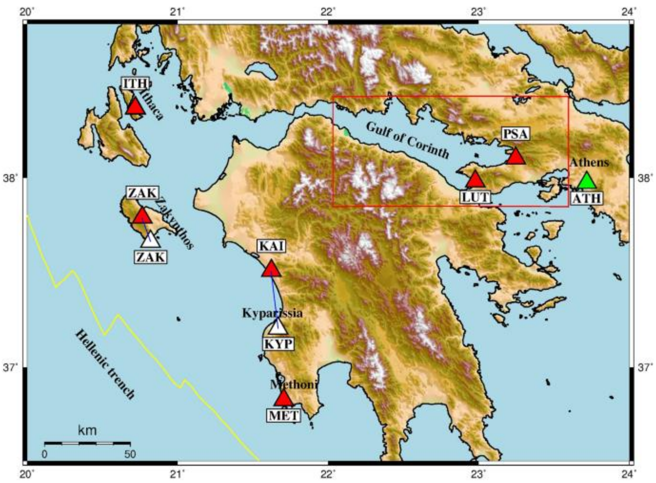


Figure 1 The gamma-ray station locations of the real-time network of NOA for soil radon concentration measurements (red triangles). Older station locations are also shown (white triangles). The alpha-particle station for Rn monitoring in the air is shown with green triangle. The region in the red rectangle includes the investigation area. The figure has been created by the "Generic Mapping Tools" GMT5.0 software (https://www.generic-mapping-tools.org/).

The installation of these stations began in May 2016 and in all sites a real-time monitoring has been established. In the areas selected, significant fault zones with dense faulting have been identified by geophysical surveys[31,32]. The first stations of the network were installed in the areas of Methoni (MET), Kyparissia (KYP) (it was recently moved 25 km to the north at a neighboring geothermal site –KAI) and Zakynthos island (ZAK). The network was later extended with two other stations, in Loutraki (LUT) and Psatha (PSA), in the region of the Eastern Gulf of Corinth. This area is of high seismic potential with a series of three major earthquakes of magnitudes M6.7, M6.4 and M6.3 occurred at 2/24/1981, 2/25/1981 and 3/4/1981. The region has major faults and has not been very active in recent years. Since 2019 a new Radon monitoring station has been established in Ithaca (ITH). The radon network was mainly based on NaI(Tl) scintillation detectors for gamma spectrometry. An alpha-particle station has been also installed in Athens for measuring the radon concentration in the air of a small tunnel (ATH). More information about the instruments is given in the chapter of Methodology.

…

Conclusions

An important observation that can be deduced from the cases we examined is that the radon variation observed along with seismicity follow a pattern similar to the stress accumulation cycle.

The form of the anomalies has features in common with several other anomalies reported in the literature such as this of the earthquake of Tashkent in 1966[8]. In the case of the extensional field of the Gulf of Corinth, a gradual increase was found in the quiescent period before the event, a sharp drop few days before the earthquake, then a stabilization at a new level until the steady rise begins again. The sharp drop in radon level before the rupture can be judged from microcracking development and the flow of radon in the activation zone that stops with the earthquake and then will relieve the extensional tenses and will stop a further radon decrease. The anomalies recorded present similar characteristics with the ones observed in laboratory experiments on samples under compressive stress[27,29], however they are of reversed polarity, which may be due to the nature of the extensive field of the study area.

Differences in recording between two neighboring stations, only one of which was installed above a fault that hosts a hydrothermal flow, suggest that deep hydrogeology may play a key role in the measurements. It is possible that the various segments of the fault zone are hydrogeologically connected to each other but also to sites with geothermal manifestations. A station installed near this fault zone's network can detect stress changes that occur in any part of it.

From the observations made at the stations of the Gulf of Corinth, it became clear that the radon changes that were detected were mostly related to the local fault zones and not distant strong events, even if they were within the radius defined by Dobrovolsky et al.[1]. This in our view is an important conclusion that can assist in the future to follow seismic events in the area and applied to other regions in Greece.

Karastathis, V.K., Eleftheriou, G., Kafatos, M. *et al.* Observations on the stress related variations of soil radon concentration in the Gulf of Corinth, Greece. *Sci Rep* **12,** 5442 (2022). https://doi.org/10.1038/s41598-022-09441-0

https://www.nature.com/articles/s41598-022-09441-0#citeas

ΕΝΔΙΑΦΕΡΟΝΤΑ - ΓΕΩΛΟΓΙΑ

How tall will Mount Everest get before it stops growing?

Arching over 8,849 metres (29,032ft) into the sky, Everest is the world's tallest mountain. But will it always be?

Harriet Constable

Aurora Elmore was approaching Mount Everest's South Base Camp in Nepal. But rather than taking the traditional 12-day hiking route, she was soaring between the frozen peaks, the rotor blades of her helicopter slicing through the thin air with a whap, whap, whap.

It was April 2019, and she was delivering supplies to a team of scientists working on the slopes of the world's tallest mountain. Her reward was a spectacular view: the day was crystal clear, exposing the entire Himalayan range.

Over the next two months, researchers on the National Geographic and Rolex expedition she helped to organise would study the effects of climate change on this part of the Himalayas. Elmore, a geologist and at the time senior programme manager of the National Geographic Society in the US, supported the team installing the world's highest weather station on the flanks of Mount Everest. During the course of their expedition, her colleagues discovered the world's highest evidence of microplastic pollution in snow and stream water close to the summit.

Gliding closer to Everest's iconic peak, Elmore got a bird's-eye view of them. A miniature city of green and yellow tents, each sheltering mountaineers headed for the top, had formed at Everest Base Camp more than 5km (3 miles) above sea level. Thousands flock to Everest every spring to make an attempt to reach the roof of the world.

And while few of the climbers would have noticed, Everest grew a tiny bit bigger during their time on the mountain.

Mount Everest, along with the rest of the Himilayas, inches further skyward every year. It raises an interesting question – with enough time, just how tall can Mount Everest grow? There are mountains on other planets in our Solar System that dwarf those on our own, so are there limits to how big a mountain can get on Earth?

Mount Everest towers 8,848.86m (29,032ft) above sea level, according to the most recent official joint survey by China and Nepal, whose borders run across its summit. But it isn't the only giant in these lands – 10 of the world's 14 peaks higher than 8,000m (26,247ft) above sea level can be found in the Himalayan range. Everest, Elmore says, is among friends. "If you've ever flown over Greenland or the Canadian Rockies you can see big mountains, but [the Himalayas] are just on another level," she says.

At more than 8,848m (29,032ft) tall, Mount Everest towers over the other giants in the Himalayas

Surrounded by so many other enormous peaks, is it possible to discern just what a monster Everest is? Elmore hesitates before answering. "It's kind of like trying to tell the tallest person on a basketball team," she says finally. "They're all tall, but which one is the teeny [bit taller]?"

The history of measuring the tallest mountain in the world stretches back to 1852. In Europe, Charles Dickens was publishing serialised instalments of his novel Bleak House. North America had started testing its first steam-powered fire engine. In Asia, the height of Mount Everest was a mystery. It was known only as "Peak XV". Radhanath Sikdar, an Indian mathematician, had been employed by the British to work on their Great Trigonometrical Survey. They wanted to gather a more accurate geographical picture of the territory they were occupying so they could control it more effectively, be it for trade or military purposes.

Sikdar used trigonometry. He measured the horizontal and vertical angles of Everest's summit from other mountaintops whose positions and heights were already known. In doing so he made a momentous discovery: the tallest mountain ever recorded. According to his calculations, the mountain stood at 8,839.8m (29,002ft) tall.

The main routes up Mount Everest have now become so popular with climbers that long queues can form

Though the technology behind measuring mountains has advanced since the 1850s, his figure was astonishingly accurate, just nine metres off the latest official height. Despite

Sikdar's findings, the mountain eventually was named after his previous boss, British surveyor Sir George Everest, who had retired several years before Sikdar's discovery.

Since then, teams have continued to work to understand Mount Everest's height. In 1954 an Indian survey determined Mount Everest to be 8,848m (29,029ft) tall, a figure which was accepted by the Nepalese government. But then, in 2005, the Chinese measured it at 8,844.43m (29,017ft) – nearly four metres (13ft) lower. In 2020, teams from China and Nepal jointly agreed upon a new officially accepted height that was 0.86m (2.8ft) higher than the Survey of India's original calculation.

While these changes in the measured height are partly due to improvements in the measuring technology available to surveyors, there has also been some politics involved. China and Nepal historically have argued over whether the snow cap on the summit should be included in the measurement or not.

But we mustn't ignore that Everest also grows a tiny little bit taller every year too.

Once, the craggy limestone peaks that skim the sky of Everest were on the ocean floor. Scientists believe it all began to change about 200 million years ago – at around the time the Jurassic dinosaurs were beginning to emerge – when the supercontinent of Pangea cracked into pieces. The Indian continent eventually broke free, journeying north across the vast swathe of Tethys Ocean for 150 million years until it smacked into a fellow continent – the one we now know as Asia – around 45 million years ago.

The crushing force of one continent hitting another caused the plate beneath the Tethys Ocean, made of oceanic crust, to slide under the Eurasian plate. This created what is known as a subduction zone. Then the oceanic plate slipped deeper and deeper into the Earth's mantle, scraping off folds limestone as it did so, until the Indian and Eurasian plates started compressing together. India began sliding under Asia, but because it's made of tougher stuff than the oceanic plate it didn't just descend. The surface started to buckle, pushing the crust and crumples of limestone upwards.

And so the Himalayan mountain range began to rise skyward. By around 15-17 million years ago, the summit of Everest had reached about 5,000m (16,404ft) and it continued to grow. The collision between the two continental plates is still happening today. India continues to creep north by 5cm (2in) a year, causing Everest to grow by about 4mm (0.16in) per year (although other parts of the Himalayas are rising at around 10mm per year [0.4in]).

But understanding how and why Everest's height changes is more complex than just this. While plate tectonics push the summit higher into the sky, erosion claws away at it.

To understand this process better, scientists studied another mountain some 8,700km (5,405 miles) away from Mount Everest, in Alaska.

Rachel Headley, an associate professor of geosciences at the University of Wisconsin-Parkside, was part of a scientific expedition to Mount Saint Elias on the border of Alaska and Canada between 2005-2008. The mission intended to understand the complex roles of tectonics and erosion in how mountains grow and shrink. The second largest mountain in both Canada and the US, Saint Elias faces the same effects as Everest, from tectonic activity to erosion, but across a far smaller, more manageable area. "In that region, Alaska, there were very particular weather patterns that had helped these large glaciers grow," Headley says. "And then both glaciers and rivers, landslides, and avalanches were all kind of the processes that connected to tear them down."

Headley's role on the team was to understand the thickness of the Seward Glacier, which runs through the Saint Elias mountains, and how fast it was moving. Both can impact the rate of erosion, which can affect how quickly a mountain's height is worn away. "If we have a thinner glacier, and it's moving super fast… we know there has to be some sliding, which we think is really important for erosion," she says. "Sliding" can cause glacial abrasion, which is when the glacier drags rock fragments across the surface as it moves, creating a sandpapering effect.

Weather can also cause significant erosion to a mountain. Elmore describes one of the weather stations she helped install during the 2019 Mount Everest expedition as being "damaged by rocks the size of cricket balls that were picked up by the wind and thrown at it". Buffetting by debris and ice picked up by the wind takes its toll after a while.

Whatever its official height is, Mount Everest inspires awe in most who stand in its shadow

Many of the highest peaks in the world, including Everest, have permanent snow caps that help protect them from this wind-blown barrage. Rock covered in a soft blanket of snow suffers less weathering and erosion than bare rock, says Headley. It also protects the rock from chemical reactions with the air that can gradually degade the minerals in the limestone that comprises much of the uppermost parts of Mount Everest. But there are still places where the rock is exposed to the elements.

"For a tall mountain range, you can basically get to such a steep angle in the rock that it can't actually support ice, and snow, and then you start to get avalanches, and you get bare rock," says Elmore. Rock falls and land slides – a constant hazard on Everest and the surrounding area – both play a role in shaving away at Everest's height, and rivers too. They have been estimated to be cutting gorges into the rock at a rate of between 4-8mm (0.2-0.3in) a year.

But the exact impact erosion has on a mountain's height is still to be understood. Some scientists believe that reducing the weight of a mountain (by taking away the snow, ice and rock it's made of) might actually allow the tectonic plates to push the, now lighter, mountain even further into the sky.

Headley's colleague Terry Pavlis, who was the lead investigator on the St Elias Erosion Tectonics Project (Steep), explains that, on a large scale, "erosion attacking a landscape allows it to rise up".

In some parts of the world, entire landmasses are still rearing up after the last ice age – something known as isostatic rebound. Parts of North America and northern Europe, includeing Scotland, are rebounding after the rocky crust there was squashed by enormous continental ice sheets that waxed and waned during the Pleistocene. According to one study by researchers at Germany's University of Postdam, up to 90% of the uplift in the European Alps can be explained by this surprisingly elastic response to the end of the ice age. Experts believe similar glacial isostatic rebound may have taken place on the Tibetan Plateau and in the Himalaya as the ice age glaciers receeded – contributing between 1-4mm (0.04-0.16in) a year to the uplift.

"But there's some kind of equilibrium between how fast that landscape can erode and how high those peaks can get," adds Pavlis.

The exact details of this equilibrium are still being explored. In a region like the Appalachians in north-eastern North America, or the Scottish Highlands, erosive forces like rivers and landslides are cutting mountains down lower and lower, Headley says. "But in regions with tectonic activity, the tectonic force can be driving the mountains up slower, faster, or at around the same rate as the erosion is cutting it down. We don't fully understand all the drivers in those types of systems."

The most recent official height for Mount Everest was agreed following Chinese and Nepalese surveying expeditions to the summit

So how are mountains actually measured nowadays? One of the most common instruments used is the Global Navigation Satellite System (GNSS), which records the precise position of the mountain peak using a network of satellites. GNSS can "measure heights to the millimetre," according to Pavlis. The challenge, for a mountain like Everest, has always been the weight of the equipment. "It's hard enough to get to the peak – try adding a 30lb (13kg) instrument," he says.

A helicopter taxi to the top with the heavy luggage is out of the question – the thin air around Everest's summit means the engine can't produce enough power and there's too much drag from the rotor blades to operate safely. The strong winds and jagged creeks also make touching down anywhere near the summit dangerous. One helicopter pilot did set a world record by touching down briefly on top of Mount Everest in 2005, but only after the manufacturer stripped it bare of every unessential item to make it feather light.

Luckily, GNSS systems have gotten smaller over the years. Now they weigh more like 1.2kg (2.6lbs) and are "about the size of a lunchbox, maybe a little smaller", says Pavlis. But the devices still need batteries, which can struggle in cold temperatures. The average temperature at the summit of Everest during the summer monsoon months is a balmy -19C. And there are other complications too. "There's an antenna that's about, you know, half a metre in diameter. And those have to be set up somehow so that they are absolutely stationary," Pavlis explains.

To gather millimetre-accurate results the instrument then has to record for several hours. In the thin air of Everest's "death zone", operating these instruments can be hazardous for surveyors. Members of a Nepalese expedition to take GNSS measurements on Everest in 2019 spent two hours on the summit – far longer than most who make their way there – after arriving at 03:00 in the pitch black and biting cold.

Another option, often used in addition to GNSS for the most accurate readings, is Ground Penetrating Radar (GPR). "GPR uses radar pulses to image below the surface, so it can tell us the thickness and internal structure of snow and ice overlying the rocks on Everest's summit," says Elmore. "There's something like 4m (13ft) of snow and ice on the top of Mount Everest, but that can change depending on the cli-mate."

While Elmore and her team were conducting their own scientific experiments on Everest they leant the Nepalese ex-pedition a GPR device so they could take measurements from the summit. "It had to be a specific design of GPR, one that was super lightweight so [it could be carried] to the top of Everest, but that also had the right transmitter and receiver to measure the ice," says Elmore. The device had recently been used at the summit of Denali, the tallest mountain in the US, so they knew it was up to the job.

Despite the many hurdles they faced, the Nepalese team's expedition to measure the height of Everest was successful. They had hoped to answer questions about whether a deadly 7.8 magnitude earthquake that hit Nepal in April 2015 had affected Mount Everest's height. Initial reports indicated the mountain had shifted 3cm (1.9in) to the south-west by the large earthquake, which killed 9,000 people and damaged hundreds of thousands of homes, but had not changed its height.

The project, however, soon became muddied with international politics. A few months later a team of Chinese surveyors conducted their own measurements during an expedition from the other side of the mountain. They had their own figure, which didn't include the snow cap. The Nepalese figure, on the other hand, did. In October 2019, the two countries decided to combine their data and in December 2020 they released the figure for the new official height – 8,848.86m (29,032ft), including the snow on top.

As China and Nepal found, deciding exactly what you measure, and how you measure, is fundamental to establishing a mountain's height. For example, to agree upon how tall a mountain is, we must first agree on where the bottom is. But that's not as easy as it might sound.

The Himalayas began rising around 45 million years ago as the Indian and Eurasian continental plates collided

For centuries mountains have been measured using sea level as the base from where their height is calculated. But the Earth is not perfectly round: it bulges along the equator. And sea level isn't static, it is pulled and changed by our planet's gravity. Plus, Everest isn't sticking out of the ocean, it's nestled among a landscape of other mountains. Many complex calculations have to be done to establish where sea level would actually be, and Everest's relative height to it. When that starting point is changed, everything changes.

But let's say scientists started their measurements from the core of the planet instead. Everest would no longer be considered the tallest mountain on Earth. The mountain that measures the greatest distance from the centre of Earth to its peak is Chimbarozo, in Equador at 10,920m (35,826ft). What about starting from the seabed? The accolade of tallest mountain would then go to Mauna Kea, a volcano in Hawaii that arches 10,000m (32,808ft) from the ocean floor.

Looking beyond our own planet, we can see examples of just how enormous mountains can become. Olympus Mons, a volcano on Mars, towers 21km (19.2 miles) into the sky and stretches 624km (388 miles) wide. It is roughly the size of the state of Arizona. Because gravity on Mars is weaker than on Earth, and because Mars doesn't have tectonic plates shifting and colliding beneath the surface, the ooze of lava that flowed out of the Martian volcano in the planet's past was able to grow to monstrous proportions.

Could Everest become a similar giant? In the 1980s, a researcher at the Cavendish Laboratory in Cambridge, UK, attempted to estimate what such a limit might be on Earth, taking into account the strength of gravity and the strength of the rock underlying the mountain. The calculations, which made "no presensions to serious geophysics" estimated the theoretical maximum height of a mountain range with a granite base – as Mount Everest largely has – to be 45km (28 miles) on Earth.

But there are a number of barriers – apart from our planet's relentless weather – that might stand in the way of this, according to Headley. For starters, "you would eventually run out of your tectonic forces, and then it would stop growing", she says. Scientists believe that eventually the Earth's mantle will cool to such a degree that the planet-wide dance of plate tectonics will end. Until then, earthquakes and landslides will also erode away the mountain too.

"At some point, [the mountain] becomes so steep that it's unstable and chunks start falling off," Elmore says.

With the wind, snow and ice buffeting, cracking and splitting the rock, Everest is unlikely to ever reach the sizes seen on Mars. "We have our weather systems, and weather is really good at creating erosional forces," Headley says. "Basically, the fact that we have water, whether in the form of ice or snow, or just rain, is what really can limit mountain growth."

For now, Everest keeps edging, bit by bit, into the sky as other forces try to tear it down. Elmore's 2019 team discovered global warming was yet another of these, driving considerable thinning of the snow and ice on the upper reaches of the mountain in recent decades and revealing more bare rock to the erosive impacts of weather.

Everest is also far from being the fastest-growing mountain on our planet. Others, such as those in the Swiss Alps, are growing more rapidly thanks to an imbalance in the amount of erosion taking place. Scientists found that uplift is more than 50 times faster than any negative effects from erosion here. But the Swiss Alps are far shorter than Mount Everest and most studies suggest the mountains there are currently growing at 2-2.5mm (0.08-0.1 inches) per year. The closest contender for the top spot is perhaps Nanga Parbat, a neighbour to Everest located in the Pakistani Himalayan range, which is 8,126m (26,660ft) tall and growing at 7mm (0.27in) per year. In 241,000 years it could overtake Everest to be the tallest mountain on Earth, provided rates of erosion don't change.

Meanwhile, Everest retains its allure as a mountain at the extreme of what can be found and endured here on Earth. Its reputation as the highest peak on our planet continues to attract climbers from all over the world, even as its height continues to shift.

Over a video call I ask Billi Bierling, a mountaineering journalist who hiked Everest herself in 2009, whether an extra millimetre, metre or mile higher matters to people like her. She is relaxing on the sofa at her mother's house in Germany, preparing to head back to Nepal for the summer season in March.

"The exact measurement doesn't matter," she says, laughing warmly at my question. "What matters is that it's the highest, and that you go to the highest point. If you're having a bad day, or someone is not very nice to you, or they put you down, you can think to yourself, you know what? I've climbed Everest."

For most who reach the summit, it is simply being there that counts.

--

(BBC Future, 14th April 2022, https://www.bbc.com/future/article/20220407-how-tall-will-mount-everest-get-before-it-stops-growing)

Geochemical ice-core constraints on the timing and climatic impact of Aniakchak II (1628 BCE) and Thera (Minoan) volcanic eruptions

Charlotte Pearson, Michael Sigl, Andrea Burke, Siwan Davies, Andrei Kurbatov, Mirko Severi, Jihong Cole-Dai, Helen Innes, Paul G Albert, Meredith Helmick

Abstract

Decades of research have focused on establishing the exact year and climatic impact of the Minoan eruption of Thera, Greece (c.1680–1500 BCE). Ice cores offer key evidence to resolve this controversy, but attempts have been hampered by a lack of multi-volcanic event synchronization between records. In this study, Antarctic and Greenland ice-core records are synchronized using a double bipolar sulfate marker and calendar dates are assigned to each eruption revealed within the 'Thera period'. From this global scale sequence of volcanic sulfate loading, we derive indications towards each eruption's latitude and potential to disrupt the climate system. Ultra-fine sampling for sulfur isotopes and tephra conclusively demonstrate a colossal eruption of Alaska's Aniakchak II as the source of stratospheric sulfate in the now precisely dated 1628 BCE ice layer. These findings end decades of speculation that Thera was responsible for the 1628 BCE event, and place Aniakchak II (52 ± 17 Tg S) and an unknown volcano at 1654 BCE (50 ± 13 Tg S) as two of the largest Northern Hemisphere sulfur injections in the last 4000 years. This opens possibilities to explore widespread climatic impacts for contemporary societies and, in pinpointing Aniakchak II, confirms that stratospheric sulfate can be globally distributed from eruptions outside the tropics. Dating options for Thera are reduced to a series of precisely dated, constrained stratospheric sulfur injection events at 1611 BCE, 1562-1555 BCE and c.1538 BCE which are all below 14 ± 5 Tg S, indicating a climatic forcing potential for Thera well below that of Tambora (1815 CE).

For the last 2,500 years, correlations between the record of volcanic sulfate in Northern Hemisphere ice cores, and growth anomalies in tree-rings indicating sudden, short-term perturbations of the climate system, are well established [1] allowing for detailed investigations of volcanic impact on human societies [2]. Exact dating of such events is of the upmost importance because multiple timelines can often be secured and linked using volcanic marker horizons, enhancing understanding of cause and effect. Further back in time, this relationship is less accurately and precisely resolved, and controversies remain over when, where, and what impact, certain eruptions had on ancient societies and ecosystems.

The Minoan eruption of Thera, (Santorini) in the Mediterranean Sea, and the period c.1680-1500 BCE, have long been a focus of such investigation [3, 4, 5, 6, 7]. This eruption, one of the more explosive of the Holocene (VEI 7 [8]), sealed the spectacular Minoan settlement of Akrotiri (on Thera) under meters of volcanic debris [9] and deposited tephra and other volcanic products across the wider region [10]. The resulting marker horizon provides an important synchronization point for chronologies of the ancient Aegean, Anatolia, Levant, and Egypt, but dating it precisely has proved difficult. Archaeological connections between these regions, founded on the historical chronology of Egypt, indicate that the eruption must have occurred after the start of the New Kingdom [11, 12, 13, 14]. This is conventionally c.1540–1500 BCE (at earliest c.1560 BCE [13] or 1550 BCE [11]) or after 1570–1544 cal BCE (95.4% probability) based on radiocarbon dating [15]. However, radiocarbon dating of materials in immediately pre or post Thera eruption contexts has been strongly argued to support a date closer to 1600 BCE [16, 17, 18]. This discrepancy can be partially explained by the impact of a radiocarbon plateau between c.1610-1540 BCE [19] and differences in approach to dating materials buried by the eruption [20, 21]. A range of other factors such as volcanic contamination of samples with 'old carbon' have also been suggested [12]. A recent study on samples derived from a Theran tsunami deposit indicate a radiocarbon based date for Thera of 'after 1611 BCE', with a seed found in close proximity to the first human remains associated with the eruption yielding calibrated probability distributions of 1612-1573 cal BCE (19.4% probability) and 1665-1501 cal BCE (76.1% probability) [10].

Ice-core evidence from both poles offers the potential to refine the dating for Thera with more accuracy, but incongruous dating schemes for different ice cores and evidence for multiple eruptions c.1680-1520 BCE [22, 23, 24] have limited progress. For example, the caldera forming Aniakchak II eruption (Alaska) has been geochemically confirmed in association with differently dated sulfate events in several Greenland ice-cores [25, 26, 27] with possible dating solutions proposed [7]. Radiocarbon evidence for this event has previously been hampered by large associated errors [28, 29] making it temporally indistinguishable from Thera on this basis, however, reservoir corrected dates from marine mollusks in a tightly constrained sediment core [30] support a date of 3572 ± 4 years . BP (c.1623 ± 4 BCE).

Between 1680-1520 BCE a number of calendar dated tree-ring growth anomalies have been identified [3, 4, 40, 5, 6, 41, 19, 42, 43]. Of these, the strongest, best replicated signal occurs in 1628/7 BCE [3, 4, 5, 42, 44]. This has long been associated with the eruption Thera [3, 4], but recently presented as a more likely candidate for Aniakchak II [7]. Other, less strongly confirmed indicators for a potential volcanic impact highlight the years 1654/3 BCE [5, 6, 7], 1560 BCE [19, 42, 43], 1554 BCE [40],1550 BCE [42], 1546, 1544 BCE [19] and 1524 BCE [6, 41].

To address these chronological, climate forcing and volcanic attribution issues, we bring together Greenland and Antarctic records, synchronizing continuous high-resolution sulfur (395 BCE to 2006 CE) [45] and sulfate (4059 BCE to 395 BCE) [35] data using layer counts, and securing this in time with dendroclimatological age constraints [7]. We present a comprehensive sequence of volcanic sulfate deposition 1680–1520 BCE and use these combined, securely dated, highly resolved data to provide additional constraints on the magnitude of sulfur injection, atmospheric sulfur life cycle, and potential source locations of the identified events. We also selected two events for high-resolution sampling, across multiple ice-core records, in order to search for tephra, clarify the association of any tephra found relative to the sulfate and, through sulfur isotope analysis, provide a more accurate estimate of the fraction of sulfate that was transported via the stratosphere [46] to improve stratospheric sulfate loading estimates. These data, along with geochemical analysis of the tephra recovered, are used to reveal consequential insights into the dating, size and climatic forcing potential of Aniakchak II and the Minoan eruption of Thera.

…

PNAS Nexus, pgac048,
https://doi.org/10.1093/pnasnexus/pgac048, Published: 29 April 2022

https://academic.oup.com/pnasnexus/advance-article/doi/10.1093/pnasnexus/pgac048/6575909?login=false

Oldest evidence of tectonic plates unearthed, sealed in ancient crystals

The oldest evidence of tectonic plates are sealed in ancient crystals

A red-gold colored zircon crystal

Tiny crystals unearthed in South Africa contain evidence of a sudden transition on the planet's surface 3.8 billion years ago.

These crystals, each no bigger than a grain of sand, show that around that time, Earth's crust broke up and began moving — a precursor to the process known as plate tectonics.

The findings offer clues about Earth's evolution as a planet, and could help answer questions about potential links between plate tectonics and the evolution of life, said study lead author Nadja Drabon, a professor of Earth and planetary sciences at Harvard University.

"Earth is the only planet that has life; Earth is the only planet that has plate tectonics," Drabon told Live Science.

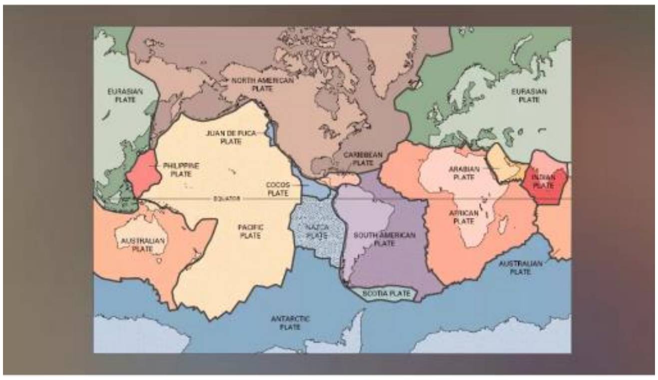
Engine of life

Nowadays, jigsaw pieces of rigid crust float on a viscous, hot ocean of magma in the mantle, Earth's middle layer. These pieces of crust grind against each other, dive beneath each other at so-called subduction zones and push each other up, creating mountains and ocean ridges, forging volcanoes and triggering the earthquakes that regularly rock the planet. The sinking of tectonic plates also produces new rocks at subduction zones, which interact with the atmosphere to suck up carbon dioxide. This process makes the atmosphere more hospitable for life and keeps the climate more stable, Drabon said.

But things weren't always this way. When Earth was young and hot, during the Hadean eon (4.6 billion to 4 billion years ago), the planet was first covered with a magma ocean and then, as the planet cooled, a solid rock surface.

Exactly when that surface cracked and pieces of it began moving has been hotly debated. Some studies estimate plate tectonics began just 800 million years ago, while others suggest this system is at least 2 billion years old, [Live Science previously reported](#).

But because the planet is constantly recycling its crust into the mantle, there are almost no ancient rocks at the surface to help settle the debate. Prior to this study, "rocks that are between 2.5 [billion] and 4 billion years old only make up 5% of the rocks at the surface," Drabon said. "And earlier than 4 billion years, there are no rocks preserved."



A map of the world's plate tectonics. Earth is the only planet known to have them.

Sudden transition

That changed in 2018, when Drabon and her colleagues discovered zircon crystals in South Africa's Green Sandstone Bed, in the Barberton Greenstone mountain range. The team found 33 zircons, ranging in age between 4.1 billion and 3.3 billion years old.

In the new study, published April 21 in the journal AGU Advances, the team analyzed different isotopes, or variants of elements with different numbers of neutrons, in those ancient zircons, as well as in many zircons from other times and places on Earth.

In the isotopes, the scientists found evidence of a sudden transition to primitive plate tectonics dating to around 3.8 billion years ago. That finding suggests that by that time, in at least one place on the planet, a simple form of subduction had begun. Whether or not this happened globally is still undetermined, and it's likely that the "really efficient engine of plates moving against each other" that exists today hadn't yet emerged, Drabon said.

Isotope analysis of elements such as oxygen, niobium and uranium also showed that rocks from the surface held water as early as 3.8 billion years ago, suggesting that the zircons were once locked in oceanic crust buried in a primeval seafloor. And extrapolating from the earliest samples, from 4.1 billion years ago, suggest that the planet had a solid crust no later than 4.2 billion years ago, Drabon said.

This would mean that Earth's magma sea persisted only until the late Hadean. Previously, "people thought that Earth was just covered by a magma ocean until 3.6 billion years" ago, Drabon said.

The new study hints that Earth's molten lava ocean existed for at most a few hundred million years before the solid crust formed, she added.

So what triggered this transition? One theory is that plate tectonics simply emerged once Earth had cooled enough, she said. It's also possible that, like a dessert spoon cracking the crisp top of a crème brûlée, massive space rocks may have slammed into Earth and shattered its crust.

Another intriguing question addresses if Earth's transition to early plate tectonics somehow helped life evolve, Drabon added.

While early fossil evidence of life on Earth dates to around 3.5 billion years ago, chemical signatures of biological processes, found in the ratio of carbon isotopes, are even older. Some can be found as far back as 3.8 billion years ago — around the same time early plate tectonics emerged, Drabon said.

(Tia Ghose / LIVESCIENCE, 30 April 2022, https://www.livescience.com/oldest-evidence-tectonic-plates)

ΕΝΔΙΑΦΕΡΟΝΤΑ - ΛΟΙΠΑ

Massive meteorite impact created the hottest mantle rock ever

The meteorite sizzled rocks some 36 million years ago.

The rock was found within the Mistastin impact crater in Labrador, Canada, shown here in this satellite image.

It's confirmed: The hottest rock ever discovered in Earth's crust really was super-hot.

The rock, a fist-sized piece of black glass, was discovered in 2011 and first reported in 2017, when scientists wrote in the journal Earth and Planetary Science Letters that it had been formed in temperatures reaching 4,298 degrees Fahrenheit (2,370 degrees Celsius), hotter than much of the Earth's mantle. Now, a new analysis of minerals from the same site reveals that this record-scorching heat was real.

The rocks melted and reformed in a meteorite impact about 36 million years ago in what is today Labrador, Canada. The impact formed the 17-mile-wide (28 kilometers) Mistastin crater, where Michael Zanetti, then a doctoral student at Washington University St. Louis, picked up the glassy rock during a Canadian Space Agency-funded study of how to coordinate astronauts and rovers working together to explore another planet or moon. (Mistastin crater looks a lot like a moon crater and is often used as a stand-in for such research.)

The chance find turned out to be an important one. An analysis of the rock revealed that it contained zircons, extremely durable minerals that crystallize under high heat. The structure of zircons can show how hot it was when they formed.

But to confirm the initial findings, researchers needed to date more than one zircon. In the new study, lead author Gavin Tolometti, a postdoctoral researcher at Western University in Canada, and colleagues analyzed four more zircons in samples from the crater. These samples came from different types of rocks in different locations, giving a more comprehensive view of how the impact heated the ground. One was from a glassy rock formed in the impact, two others from rocks that melted and resolidified, and one from a sedimentary rock that held fragments of glass formed in the impact.

The results, published April 15 in the journal Earth and Planetary Science Letters, showed that the impact-glass zircons were formed in at least 4,298 F heat, just as the 2017 research indicated. In addition, the glass-bearing sedimentary rock had been heated to 3,043 F (1,673 C). This broad range will help researchers narrow down places to look for the most super-heated rocks in other craters, Tolometti said in a statement.

"We're starting to realize that if we're wanting to find evidence of temperatures this high, we need to look at specific regions instead of randomly selecting across an entire crater," he said.

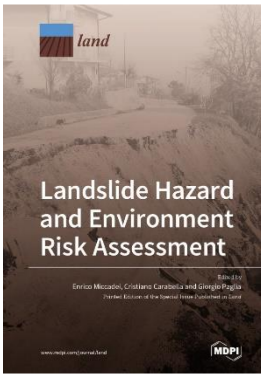
The researchers also found a mineral called reidite within zircon grains from the crater. Reidites form when zircons undergo high temperatures and pressures, and their presence allows the researchers to calculate the pressures experienced by the rocks in the impact. They found that the impact introduced pressures of between 30 and 40 gigapascals. (Just one gigapascal is 145,038 pounds per square inch of pressure.) This would have been the pressure at the edges of the impact; at the zone where the meteorite hit the crust directly, the rocks would have not just melted, but vaporized.

The findings can be used to extrapolate to other craters on Earth – and elsewhere. The researchers hope to use similar methods to study rocks brought back from impact craters on the moon during the Apollo missions.

"It can be a step forward to try and understand how rocks have been modified by impact cratering across the entire solar system," Tolometti said.

(Stephanie Pappas / LIVE SCIENCE, 18.04.2022, https://www.livescience.com/hottest-rock-on-earth-mantle)

ΝΕΕΣ ΕΚΔΟΣΕΙΣ ΣΤΙΣ ΓΕΩΤΕΧΝΙΚΕΣ ΕΠΙΣΤΗΜΕΣ

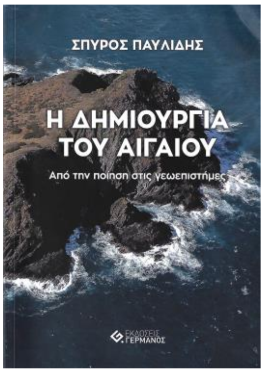


Landslide Hazard and Environment Risk Assessment

Enrico Miccadei, Cristiano Carabella and Giorgio Paglia (Eds.)

This book presents a print version of the Special Issue of the journal Land dedicated to "Landslide Hazard and Environment Risk Assessment" (Landslide Hazard and Environment Risk Assessment, *Land*). The overall goal of this Special Issue was to present innovative approaches for the analysis and mapping of landslide phenomena. Methodologies for landslide susceptibility mapping, slope stability and environmental risk management in mass-movement-prone areas, and multidisciplinary approaches for landslide analysis in different geomorphological/morphostructural environments were the main research and targets that the papers published in this Special Issue aimed to address. In the twelve papers collected in this volume, interested readers will find a collection of scientific contributions providing a sample of the state-of-the-art and forefront research in these fields. Among the articles published in the Special Issue, the geographic distribution of the case studies is wide enough to attract the interest of an international audience of readers. The articles collected here will hopefully provide useful insights into advancements in scientific approaches for the landslide susceptibility mapping and slope stability at both the local and regional scales, highlighting new ideas and innovations in the analysis of various types of mass movements (e.g., DGSDs, snow avalanches, shallow landslides, and complex and historical landslides).

(MDPI Books, April 2022)



Η Δημιουργία του Αιγαίου

Από την ποίηση στις γεωεπιστήμες

Σπύρης Παυλίδης

«Ο πολιτισμός μας κάνει ένα ανόητο λάθος όταν διατηρεί αποστάσεις μεταξύ επιστήμης και ποίησης: και τα δύο είναι εργαλεία με τα οποία μπορούμε να δούμε καλύτερα την πολυπλοκότητα και την ομορφιά του κόσμου» γράφει ο Ιταλός θεωρητικός φυσικός και συγγραφέας Carlo Rovelli.

Ο Οδυσσέας Ελύτης αναφέρει πως «*'Ενα τοπίο δεν είναι όπως το αντιλαμβάνονται μερικοί, κάποιο, απλώς, σύνολο γης, φυτών και υδάτων. Είναι η προβολή της ψυχής ενός λαού πάνω στην ύλη. Τα φυσικά στοιχεία, οι βράχοι, τα δένδρα, οι θαλασ-σες, που φλέγονται κάτω από τον ίδιο ήλιο και κατοικούνται από τις ίδιες υπερφυσικές δυνάμεις.*»

Τόσο ο ποιητής όσο κι ο επιστήμονας έχουν ως αντικείμενο πραγμάτευσής τους τον άνθρωπο και τη Φύση. Κινητήρια δύναμη είναι ένα «γιατί» μια εσωτερική ανάγκη αναζήτησης.

Γη και δημιουργία ενός τόπου . . . **διάλογος ενός λαού με το περιβάλλον** . . . η γεωλογική δημιουργία του Αιγαίου ακολουθώντας την πορεία της "Γένεσις" του "Άξιον Εστί" του Ελύτη, ποίηση, μύθος, φιλοσοφία και επιστημονική προσέγγιση είναι το αντικείμενο αυτού του βιβλίου.

Ένα χρέος πρέπει να βαραίνει κάθε ολοκληρωμένο επιστήμονα. Περισσότερο από κάθε άλλη φορά σήμερα, στην εποχή της γνώσης και της πληροφορίας, ο σημερινός επιστήμονας είναι πλέον ανάγκη να στοχάζεται πάνω στην ειδικότητά του, αλλά και πέραν αυτής, για τις νέες ιδέες που απορρέουν από την επιστήμη του, για παλιά και νέα προβλήματα που απασχολούν την ανθρώπινη σκέψη. Είναι πολύ σημαντικό να δώσουμε στον κόσμο την ευκαιρία να αποκτήσει τις εμπειρίες από τις προσπάθειες της επιστημονικής έρευνας.

(Εκδόσεις ΓΕΡΜΑΝΟΣ, Απρίλιος 2022)

ΗΛΕΚΤΡΟΝΙΚΑ ΠΕΡΙΟΔΙΚΑ

www.issmge.org/publications/issmge-bulletin/vol-16-issue-2-april-2022

Κυκλοφόρησε το Τεύχος 2 / Τόμος 16 Απριλίου 2022 του ISSMGE Bullein με τα ακόλουθα πριεχόμενα:

- **1 Message from Editor-in-Chief**
- **3 ISSMGE Time Capsule Project**
- **4 TC corner**
  - TC305 meeting
  - TC107 meeting
- **Conference reports**
  - 3rd Russian Geotechnical Forum
  - International Scientific and Practical Conference
- **Hot news**
- **Event Diary**
- **Corporate Associates**
- **Message from Corporate Associates**
- **Foundation Donors**

cs so

https://about.ita-aites.org/news

Κυκλοφόρησε το Τεύχος Αρ. 76, Απριλίου 2022 των NEWS της ITA με τα ακόλουθα περιεχόμενα:

- MESSAGE FROM JINXIU (JENNY) YAN, ITA PRESIDENT
- ITACET Online Lunchtime Series #14
- ITAtech launched a new Activity Group on Low carbon concrete linings for shafts and tunnels
- First Breakthrough of India biggest Hydroshield TBM
- Robbins Main Beam finishes challenging China drive
- WUF 11: World Urban Forum "Transforming our Cities for a better Urban Future"
- 4th International Tunneling Forum
- WTC 2022: 5 months left!
- Focus on the Danish infrastructure plan in conjunction with the WTC
- Dramix 4D inside
- Newly launched high-performance formulated soil conditioners
- CYBER AGORA #6: UNDERGROUND URBANISM
- Conference on Computational Methods and Information Models in Tunneling (EURO:TUN)

cs so

Κυκλοφόρησε το IGS Newsletter της International Geosynthetics Society με τα ακόλουθα περιεχόμενα:

IGS NEWSLETTER – April 2022

Helping the world understand the appropriate value and use of geosynthetics

httpwww.geosyntheticssociety.org/newsletters

- IGS Elections 2022: Voting Email Coming Soon! READ CANDIDATE BIOS, FAQs
- Geotextiles & Geomembranes Journal Call For Abstracts READ MORE
- New Deadline For GeoAsia7 Abstracts (Now a Hybrid Event!) READ MORE
- TC-Hydraulics Webinar: Recent Advances in Geotextile Filtration Design REGISTER
- TC-Barriers Webinar: GRI-GM13 Update REGISTER
- 10 Questions With… Jonathan Shamrock READ MORE
- My Engineer Life With… Preanca Appanna READ MORE
- igs FOUNDATION: Founding Donor Boost To IGS Foundation READ MORE
- Geogrid Reinforced Soil Retaining Wall in Chinese High-Speed Railway Embankment READ MORE
- IGS Hits 4,000 Followers On LinkedIn READ MORE, FOLLOW US!
- Upcoming Webinars
  - Studi Eksperimental Geocell Sebagai Perkuatan Lereng dan Perkerasan Jalan (Bahasa Indonesia), April 20 REGISTRATION INFORMATION
  - Recent Advances in Geotextile Filtration Design, April 26 REGISTRATION INFORMATION
  - GRI-GM13 Update, April 27 (repeated May 11) REGISTRATION INFORMATION
  - Geosynthetic Performance Testing and Integration of Results, April 28 REGISTRATION INFORMATION
- Calendar of Events

https://www.icevirtuallibrary.com/toc/jgein/29/2

Κυκλοφόρησε το Τεύχος 2 του Τόμου 29 (Απριλίου 2022) του Geosynthetics International της International Geo-synthetics Society με τα ακόλουθα περιεχόμενα:

Last words from the former Chairman of the Editorial Board, J. P. Giroud, 29(2), pp. 113

Foreword to special issue on 11th International Conference on Geosynthetics (11ICG), R. J. Bathurst, 29(2), pp. 114

Introduction to Special Issue on the 11th International Conference on Geosynthetics (11ICG), C. Yoo, Y. H. Jung, 29(2), pp. 115

Laterally-loaded pile-MSE wall system performance under different design configurations, W. Mohammed, J. Han, 29(2), pp. 116–136

Effect of internal drainage on deformation behavior of GRS wall during rainfall, C. Yoo, A. Tabish, J. W. Yang, Q. Abbas, J. S. Song, 29(2), pp. 137–150

Damage of geotextile due to impact of stones, A. Bezuijen, E. Izadi, 29(2), pp. 151–162

Shaking table tests on bridge abutments reinforced by EPS and geogrid, H. Kyokawa, Y. Yamazaki, J. Koseki, T. Konami, T. Nishi, T. Kubota, 29(2), pp. 163–173

https://www.sciencedirect.com/journal/geotextiles-and-geomembranes/vol/50/issue/2

Κυκλοφόρησε το Τεύχος 2 του Τόμου 50 (Απριλίου 2022) του Geotextiles and Geomembrabes της International Geo-synthetics Society με τα ακόλουθα περιεχόμενα:

Editorial Board, Page ii

Laudatio for Editor-in-Chief R. Kerry Rowe, Page iii

Regular Articles

Fate and transport of particle matter during GEOTextile tube dewatering of a dioxin and furan (PCDD/F) contaminated sediment, Masoumeh Alimohammadi, Craig Lake, Pages 203-215

Numerical study of strain development in high-density polyethylene geomembrane liner system in landfills using a new constitutive model for municipal solid waste, Wu Gao, Edward Kavazanjian, Xuan Wu, Pages 216-230

Method for calculating horizontal drain induced non-linear and large strain degree of consolidation, Jin-chun Chai, Jun Wang, Wenqi Ding, Yafei Qiao, Pages 231-237

The short-term and creep mechanical behaviour of clayey soil-geocomposite drainage layer interfaces subjected to environmental loadings, Zhiming Chao, Gary Fowmes, Pages 238-248

Numerical analysis of a double layer rubber dam, Xin Gao, Wei Guo, Yuxiao Ren, Wenqian Zeng, Pages 249-261

Role of particle shape on the shear strength of sand-GCL interfaces under dry and wet conditions, Anjali G. Pillai, Madhavi Latha Gali, Pages 262-281

Mitigation of track buckling in transition zones of steel bridges by geotextile reinforcement of the ballast layer, Amin Miri, Jabbar Ali Zakeri, David P. Thambiratnam, T.H.T. Chan, Pages 282-292

Filtration performance of non- woven geotextiles with internally-stable and -unstable soils under dynamic loading, M.W. Khan, A.R. Dawson, A.M. Marshall, Pages 293-311

Characterisation of geomembrane and geotextile interface short-term creep behaviour in a dry condition, Yi Lu, Hossam Abuel-Naga, Eng-Choon Leong, Wei-Guo Jiao, Xing Wang, Pages 312-322

Working mechanism of a new wicking geotextile in roadway applications: A numerical study, Chuang Lin, Xiong Zhang, Javad Galinmoghadam, Yipeng Guo, Pages 323-336

Effect of coating optimization on performances of glass fiber geogrid for semi-rigid base asphalt pavement, Gaowang Zhang, Hongliang Zhang, Wenpu Sun, Pages 337-346

Uni and bi-directional dewatering behaviour of open geotextile containers used for filtration of waste slurries, Rodrigo A. e Silva, Delma Vidal, Pages 347-356

Analytical solution for calculation of pull out force-deformation of geosynthetics reinforcing unsaturated soils, Mahmoud Ghazavi, Omid Bavandpouri, Pages 357-369

ΕΚΤΕΛΕΣΤΙΚΗ ΕΠΙΤΡΟΠΗ ΕΕΕΕΓΜ (2019 – 2023)

ΕΕΕΕΓΜ

Τομέας Γεωτεχνικής
ΣΧΟΛΗ ΠΟΛΙΤΙΚΩΝ ΜΗΧΑΝΙΚΩΝ
ΕΘΝΙΚΟΥ ΜΕΤΣΟΒΙΟΥ ΠΟΛΥΤΕΧΝΕΙΟΥ
Πολυτεχνειούπολη Ζωγράφου
15780 ΖΩΓΡΑΦΟΥ

Τηλ. 210.7723434
Τοτ. 210.7723428
Ηλ-Δι. secretariat@hssmge.gr ,
geotech@central.ntua.gr
Ιστοσελίδα www.hssmge.org (υπό κατασκευή)

«ΤΑ ΝΕΑ ΤΗΣ ΕΕΕΕΓΜ» Εκδότης: Χρήστος Τσατσανίφος, τηλ. 210.6929484, τοτ. 210.6928137, ηλ-δι. ctsatsanifos@pangaea.gr, editor@hssmge.gr, info@pangaea.gr

«ΤΑ ΝΕΑ ΤΗΣ ΕΕΕΕΓΜ» «αναρτώνται» και στην ιστοσελίδα www.hssmge.gr